BSB 663
Image Processing

May. 14, 2013

Erkut Erdem

Edge Preserving Image Smoothing

Acknowledgement: The slides are adapted from the course "A Gentle Introduction to Bilateral Filtering and its Applications" given by Sylvain Paris, Pierre Kornprobst, Jack Tumblin, and Frédo Durand (http://people.csail.mit.edu/sparis/bf_course/)

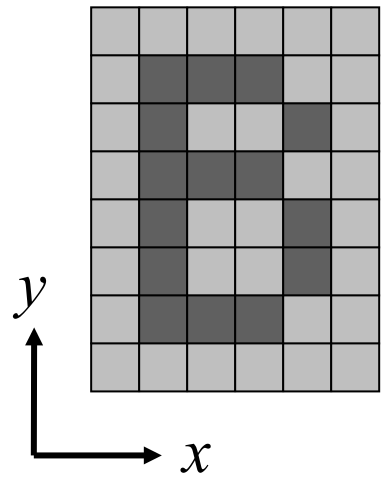
Review - Smoothing and Edge Detection

- While eliminating noise via smoothing, we also lose some of the (important) image details.
  - Fine details
  - Image edges
  - etc.
- What can we do to preserve such details?
  - Use edge information during denoising!
  - This requires a definition for image edges.

Chicken-and-egg dilemma!

- Edge preserving image smoothing

Notation and Definitions



- Image = 2D array of pixels
- Pixel = intensity (scalar) or color (3D vector)
- $I_{\mathbf{p}}$ = value of image I at position: $\mathbf{p} = (\, p_x \, , p_y \,)$
- $F\,[\,I\,]$ = output of filter F applied to image I

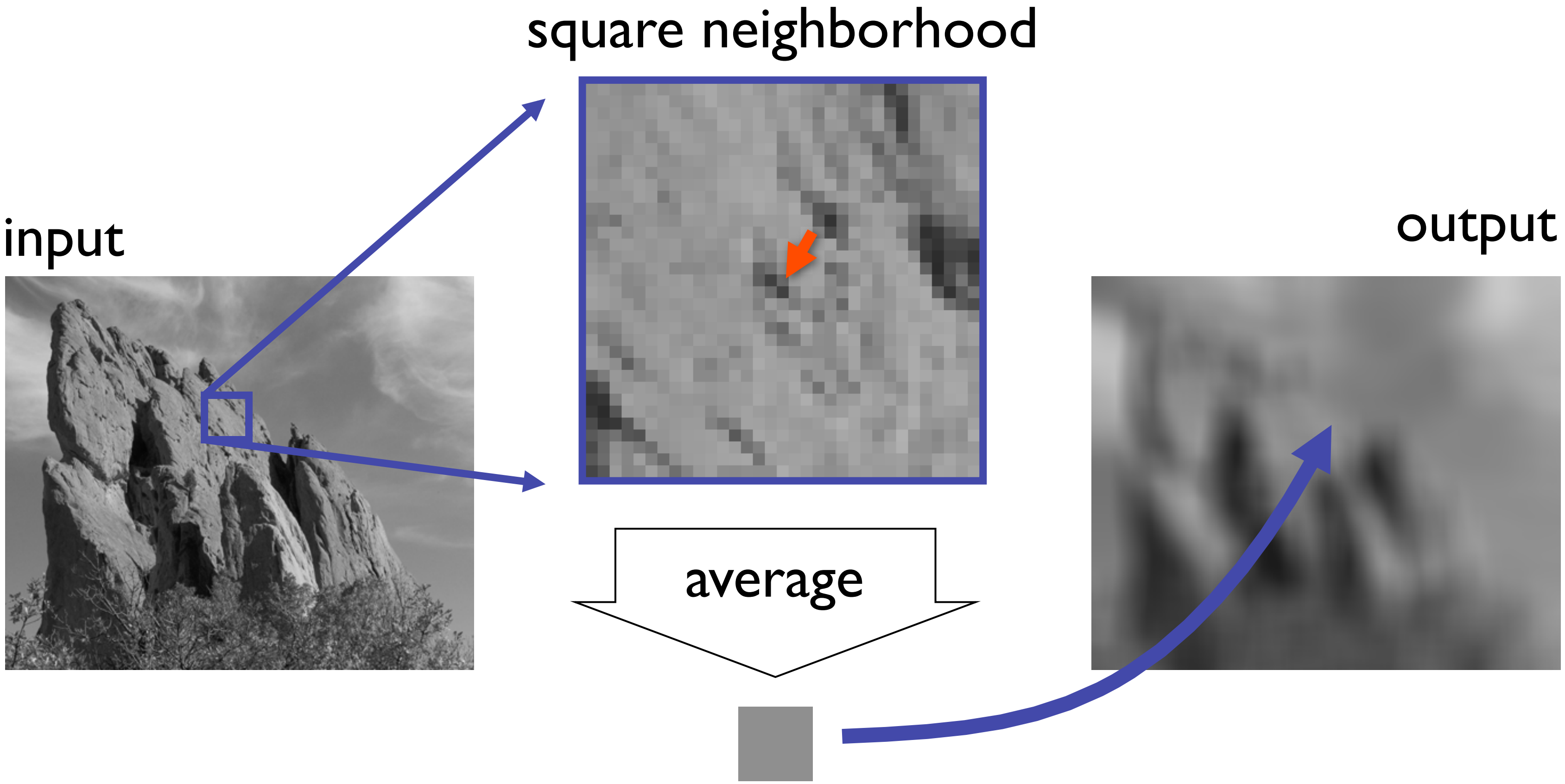
Strategy for Smoothing Images

- Images are not smooth because
  adjacent pixels are different.

- Smoothing = making adjacent pixels
  look more similar.

- Smoothing strategy
  pixel average of its neighbors

Box Average



Equation of Box Average

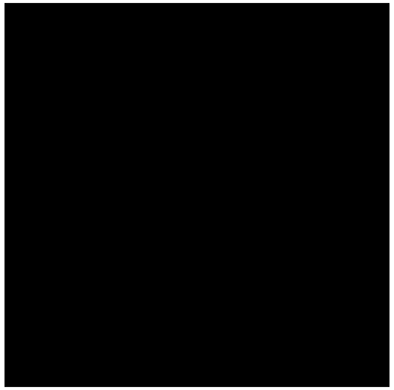
$$BA[I]_{\mathbf{p}} = \sum_{\mathbf{q}\in S} B_{\sigma}(\mathbf{p}-\mathbf{q})\, I_{\mathbf{q}}$$

result at pixel **p**

sum over all pixels **q**

intensity at pixel **q**

normalized box function



Square Box Generates Defects

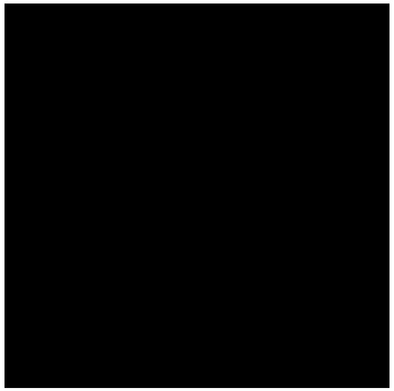
- Axis-aligned streaks
- Blocky results

input

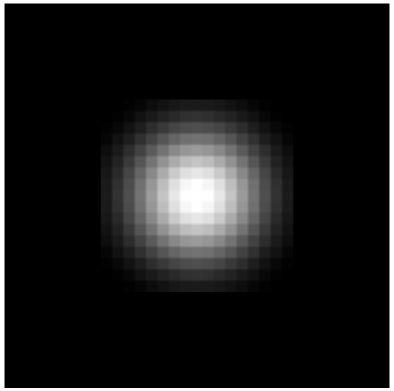
output

Strategy to Solve these Problems

- Use an isotropic (*i.e.* circular) window.
- Use a window with a smooth falloff.

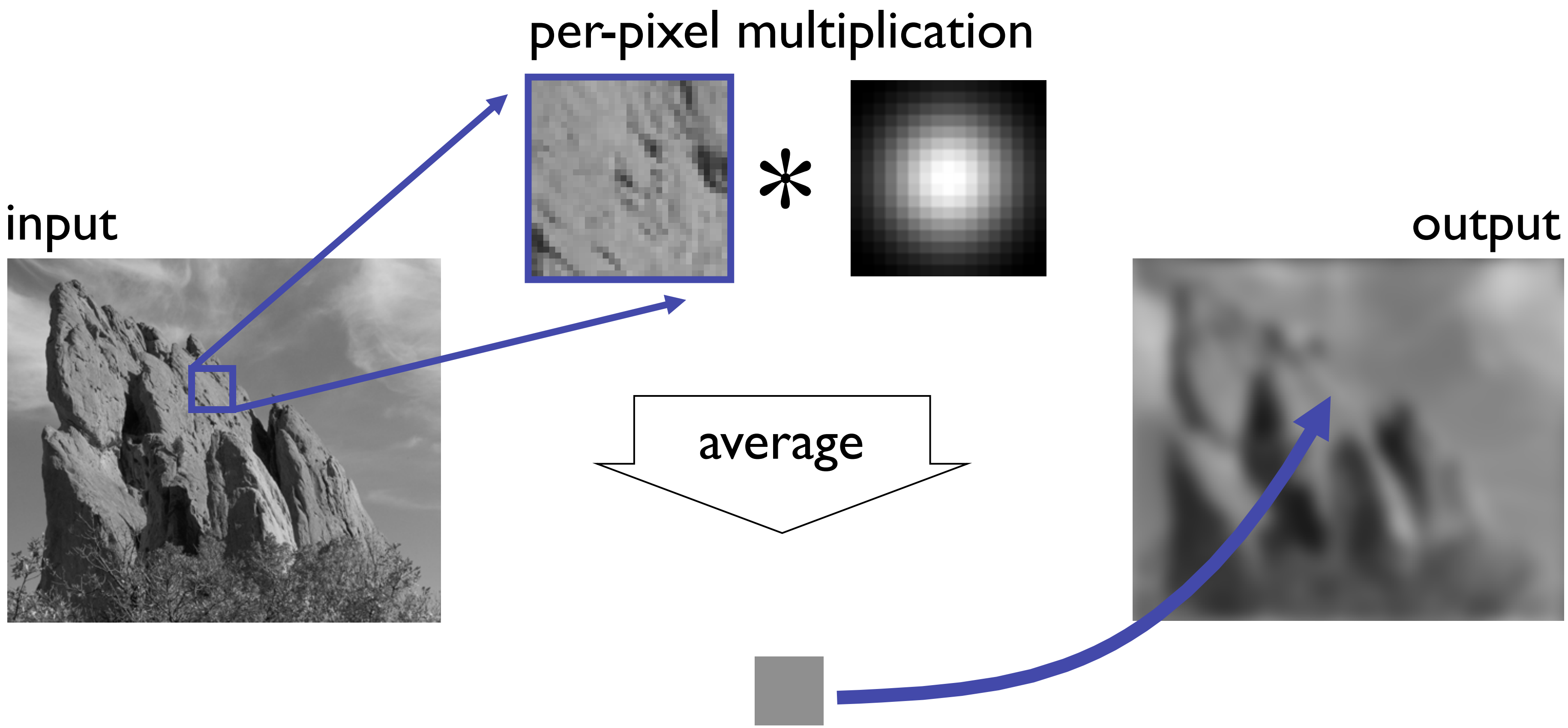


box window



Gaussian window

Gaussian Blur




input


box average

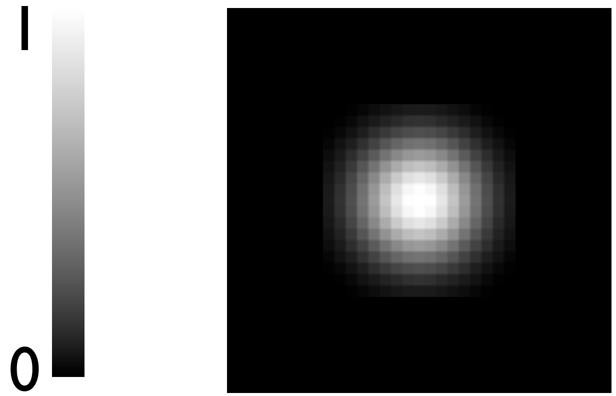

Gaussian blur

Equation of Gaussian Blur

Same idea: **weighted average of pixels**.

$$GB[I]_{\mathbf{p}} = \sum_{\mathbf{q} \in S} \boxed{G_\sigma(\|\mathbf{p}-\mathbf{q}\|)}\, I_{\mathbf{q}}$$

normalized
Gaussian function

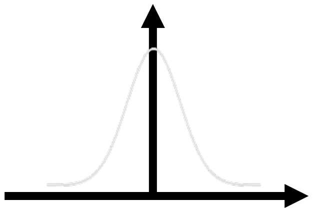


Spatial Parameter

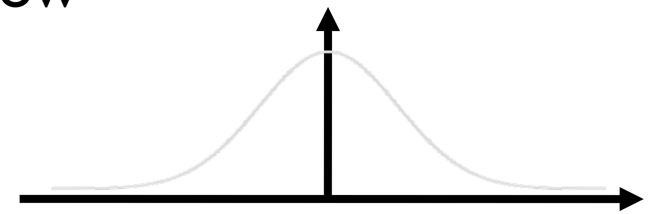
input

$$GB[I]_{\mathbf{p}} = \sum_{\mathbf{q}\in S} G_{\boxed{\sigma}}(\|\mathbf{p}-\mathbf{q}\|)\, I_{\mathbf{q}}$$

size of the window

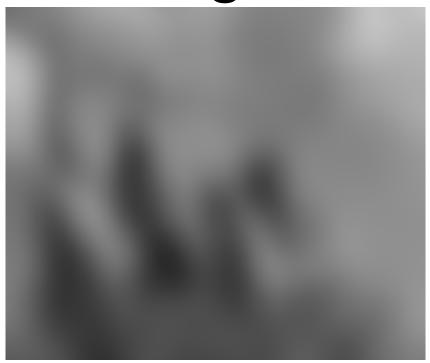


small *s*



large *s*

limited smoothing



strong smoothing

How to set *s*

- Depends on the application.

- Common strategy: proportional to image size
  - e.g. 2% of the image diagonal
  - property: independent of image resolution

Properties of Gaussian Blur

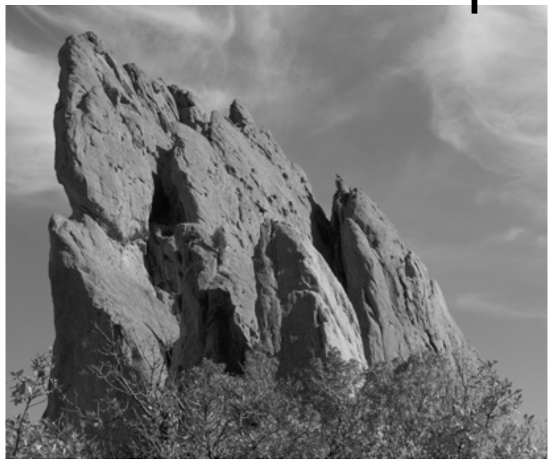
- Weights independent of spatial location
  - linear convolution
  - well-known operation
  - efficient computation (recursive algorithm, FFT…)

Properties of Gaussian Blur

- Does smooth images
- But smoothes too much:
  edges are blurred.
  - Only spatial distance matters
  - No edge term

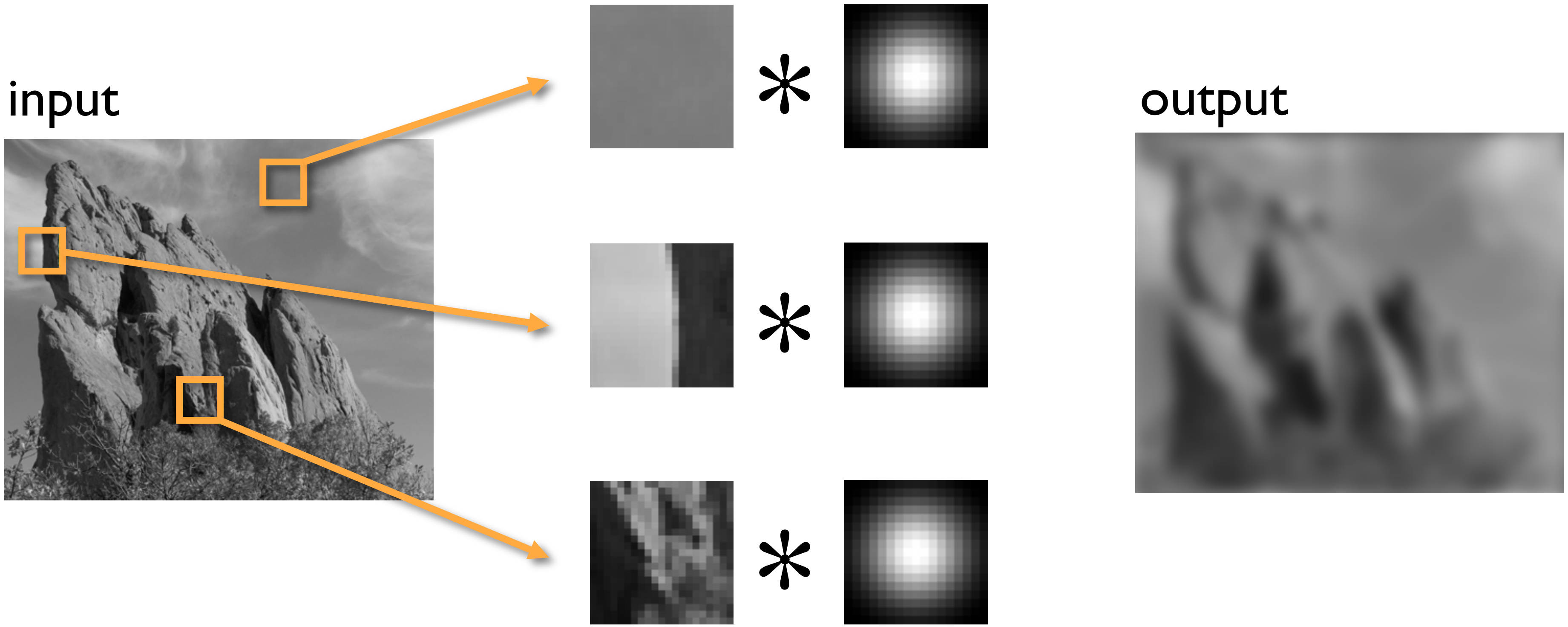
$$GB[I]_{\mathbf{p}} = \sum_{\mathbf{q}\in S} \underbrace{G_{\sigma}(\| \mathbf{p}-\mathbf{q} \|)}_{\text{space}} I_{\mathbf{q}}$$

input



output

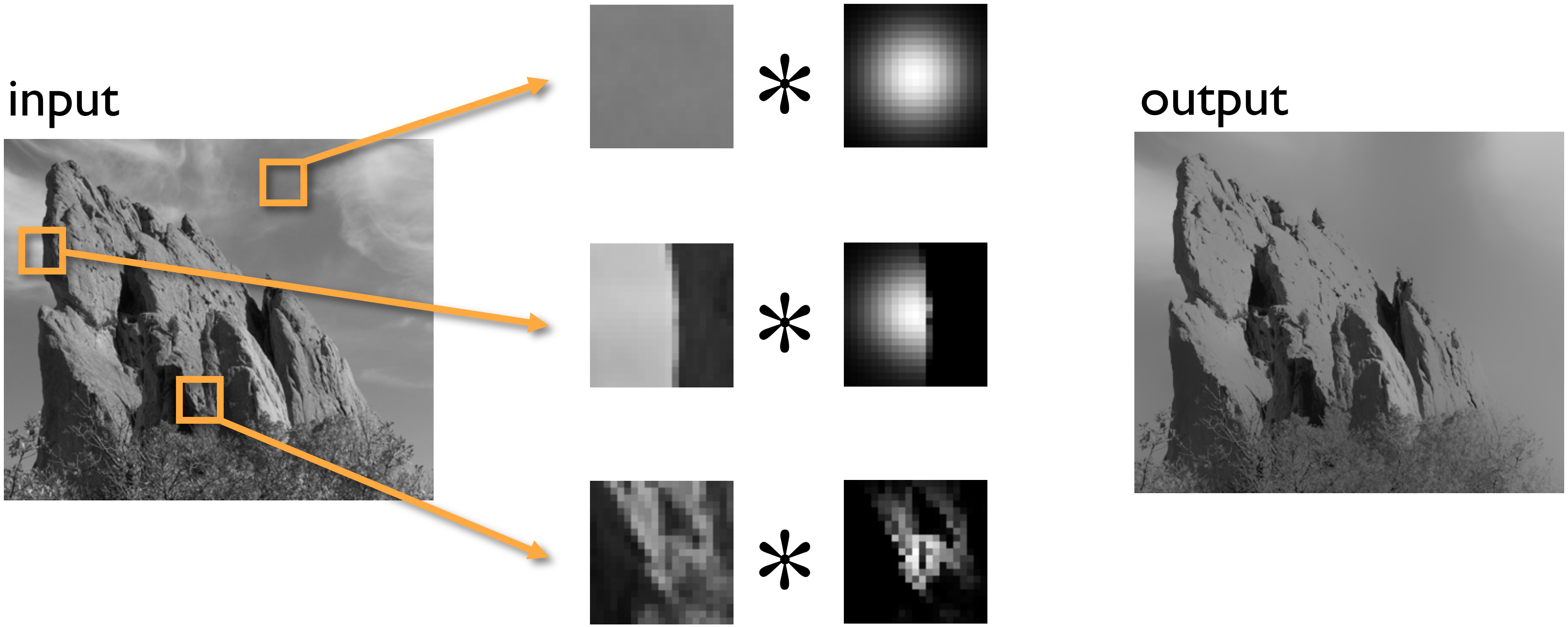
Blur Comes from Averaging across Edges



Same Gaussian kernel everywhere.

[Aurich 95, Smith 97, Tomasi 98]

Bilateral Filter
No Averaging across Edges



The kernel shape depends on the image content.

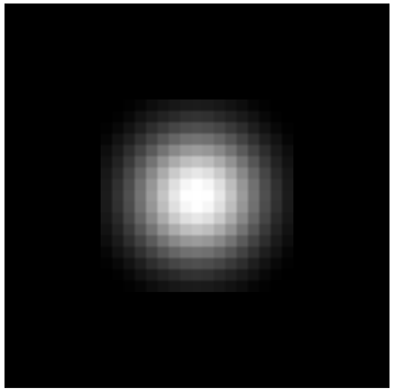
Bilateral Filter Definition: an Additional Edge Term

Same idea: **weighted average of pixels.**

$$BF[I]_{\mathbf{p}} = \overset{\text{new}}{\boxed{\frac{1}{W_{\mathbf{p}}}}} \sum_{\mathbf{q}\in S} \overset{\text{not new}}{\boxed{G_{\sigma_{\mathrm{s}}}(\| \mathbf{p}-\mathbf{q} \|)}}\, \overset{\text{new}}{\boxed{G_{\sigma_{\mathrm{r}}}(| I_{\mathbf{p}}-I_{\mathbf{q}} |)}}\, I_{\mathbf{q}}$$

normalization factor

space weight



range weight

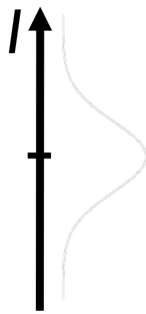
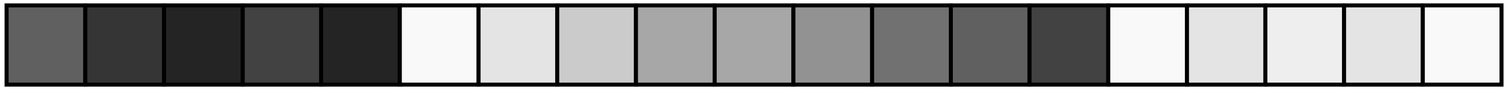
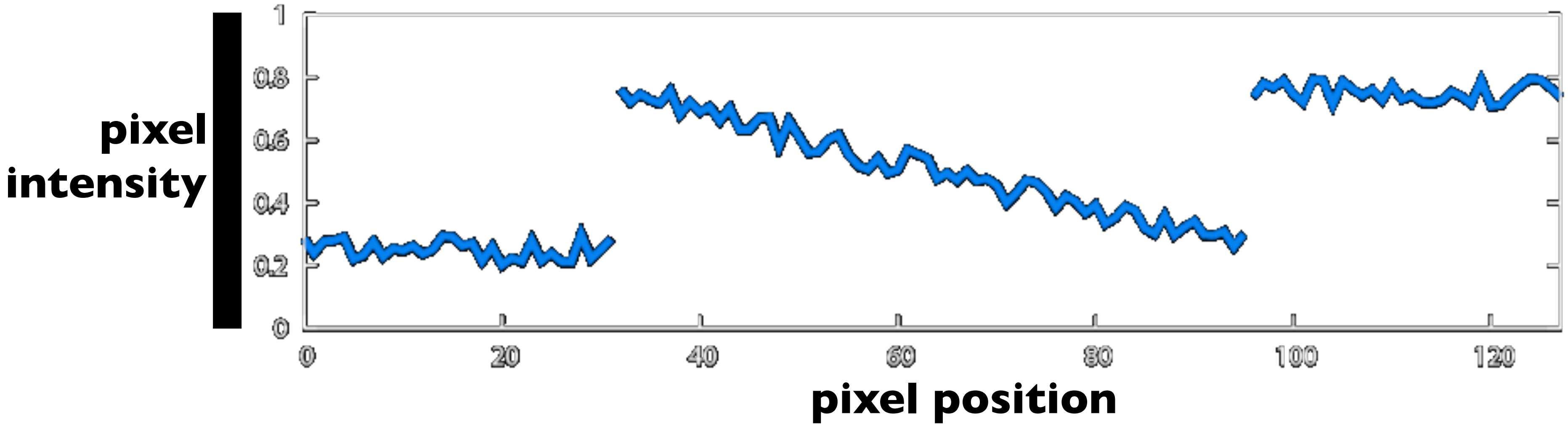


Illustration a 1D Image

- 1D image = line of pixels

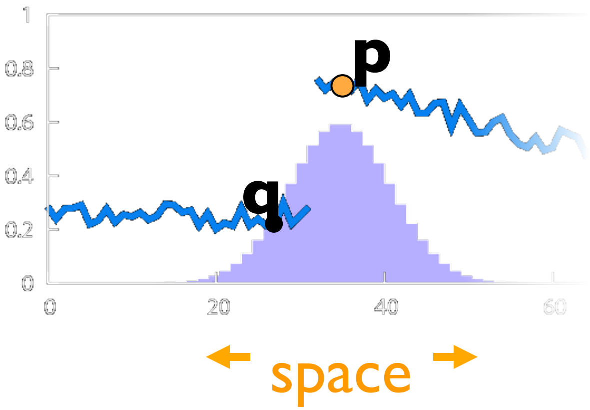


- Better visualized as a plot



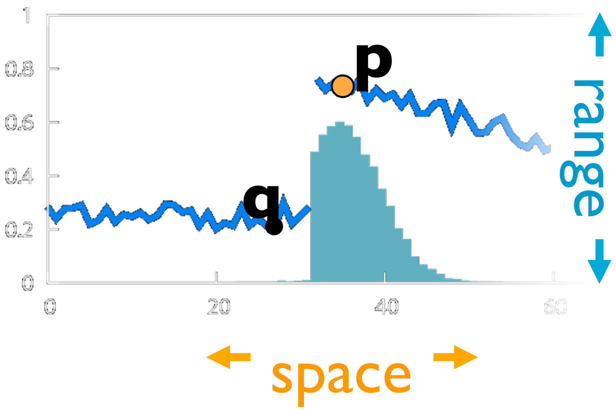
Gaussian Blur and Bilateral Filter

Gaussian blur



Bilateral filter

[Aurich 95, Smith 97, Tomasi 98]

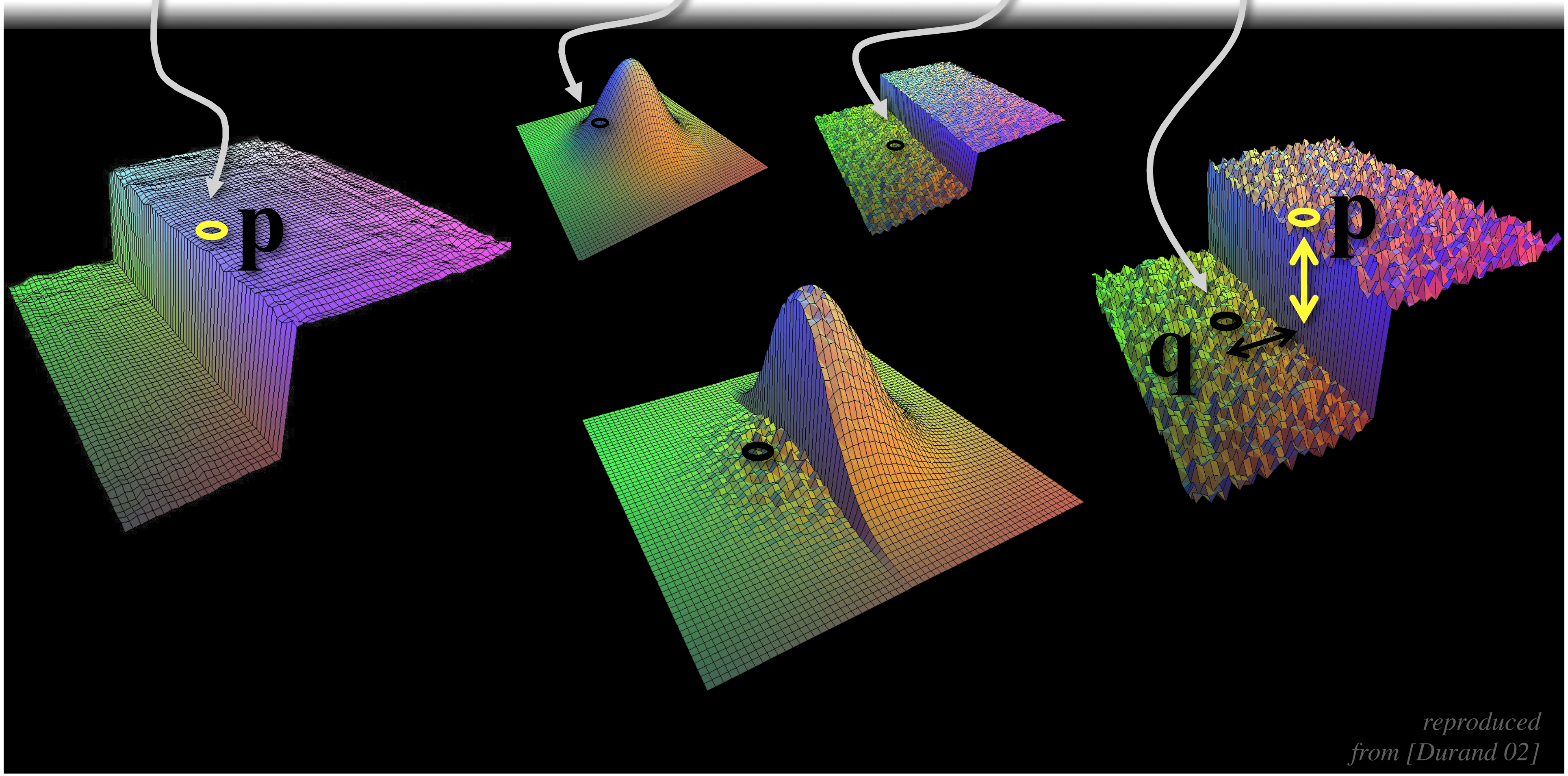


$$GB[I]_{\mathbf{p}} = \sum_{\mathbf{q} \in S} \underbrace{G_{\sigma}(\|\mathbf{p}-\mathbf{q}\|)}_{\text{space}} I_{\mathbf{q}}$$

$$BF[I]_{\mathbf{p}} = \underbrace{\frac{1}{W_{\mathbf{p}}}}_{\text{normalization}} \sum_{\mathbf{q} \in S} \underbrace{G_{\sigma_{\mathrm{s}}}(\|\mathbf{p}-\mathbf{q}\|)}_{\text{space}} \underbrace{G_{\sigma_{\mathrm{r}}}(|I_{\mathbf{p}} - I_{\mathbf{q}}|)}_{\text{range}} I_{\mathbf{q}}$$

Bilateral Filter on a Height Field

$$BF[I]_{\mathbf{p}} = \frac{1}{W_{\mathbf{p}}} \sum_{\mathbf{q} \in S} G_{\sigma_s}(\|\mathbf{p}-\mathbf{q}\|) \; G_{\sigma_r}(|I_{\mathbf{p}} - I_{\mathbf{q}}|) \; I_{\mathbf{q}}$$



Space and Range Parameters

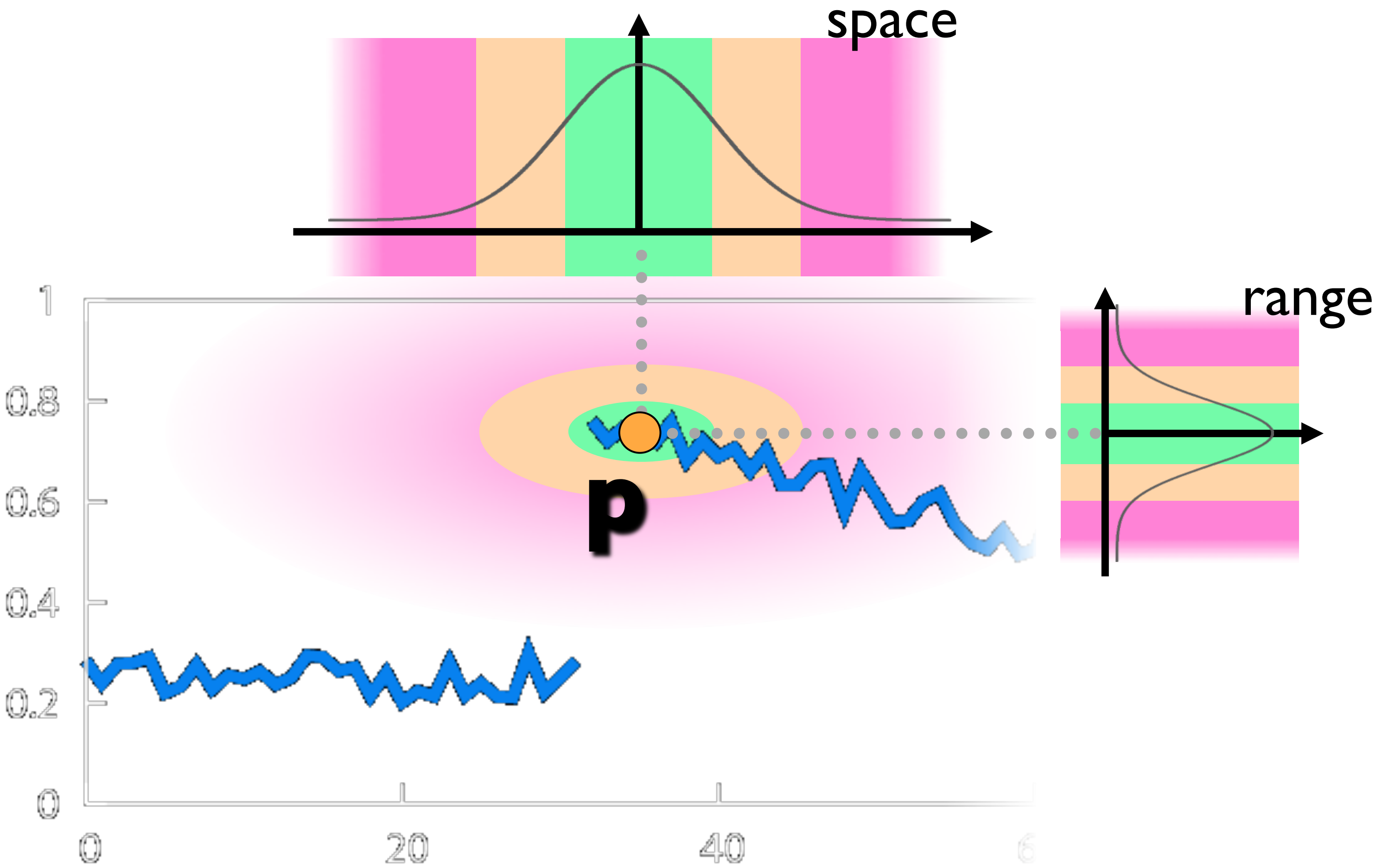
$$BF[I]_{\mathbf{p}} = \frac{1}{W_{\mathbf{p}}} \sum_{\mathbf{q} \in S} G_{\sigma_{\mathrm{s}}}(\| \mathbf{p} - \mathbf{q} \|) \, G_{\sigma_{\mathrm{r}}}(| I_{\mathbf{p}} - I_{\mathbf{q}} |) \, I_{\mathbf{q}}$$

- space σ_{s} : spatial extent of the kernel, size of the considered neighborhood.

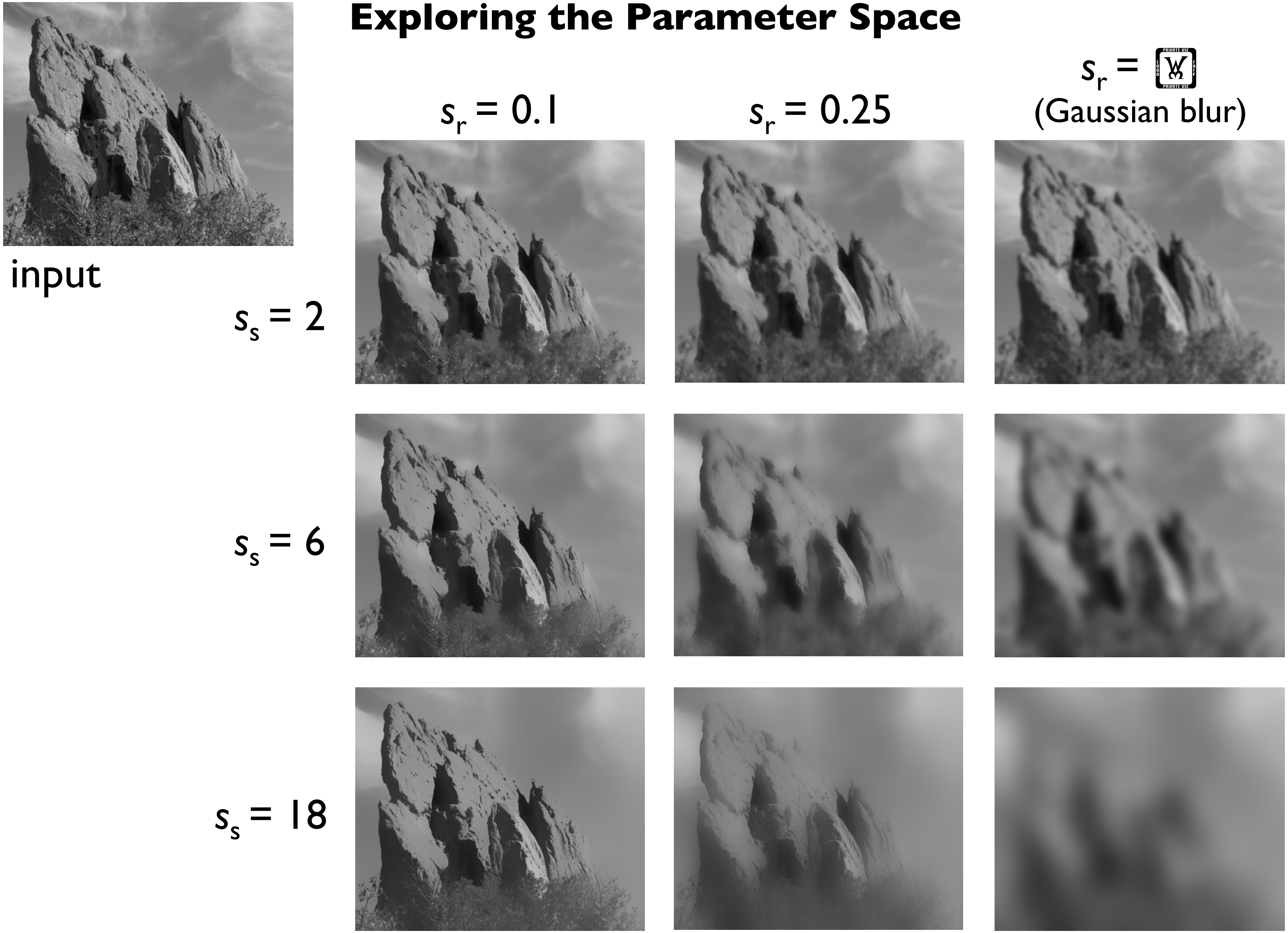
- range σ_{r} : “minimum” amplitude of an edge

Influence of Pixels

Only pixels close in space and in range are considered.

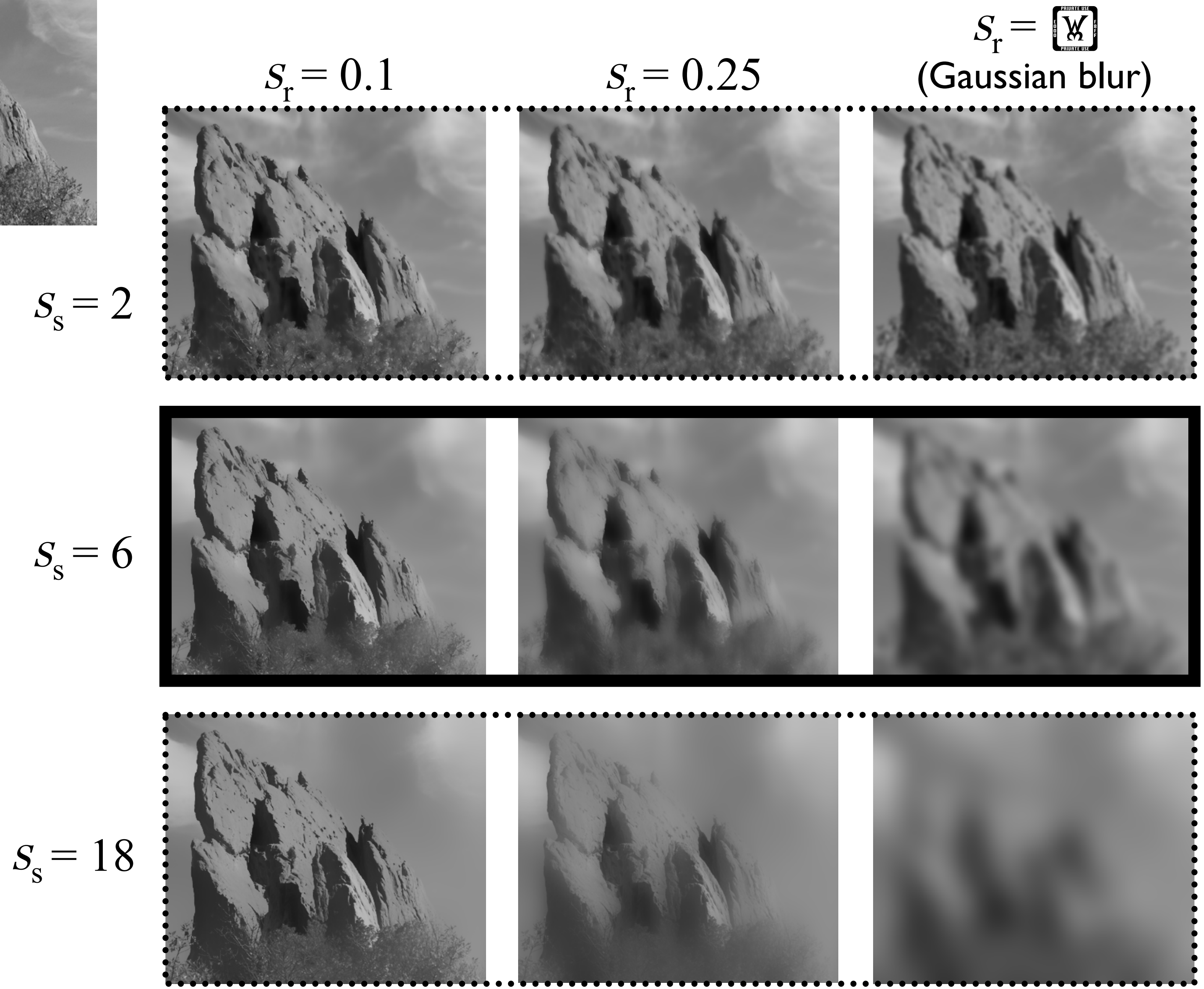


Exploring the Parameter Space



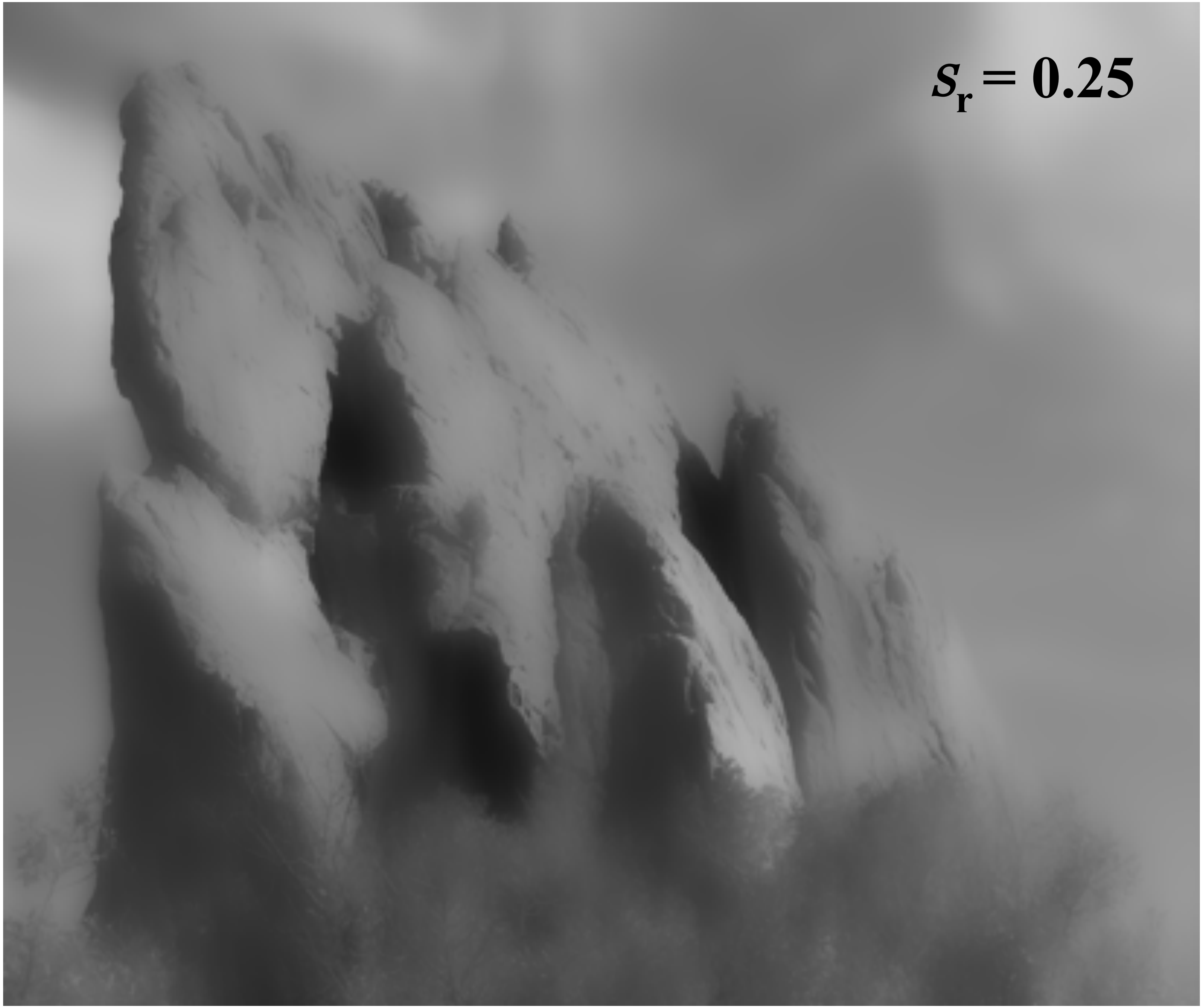
Varying the Range Parameter

input




input

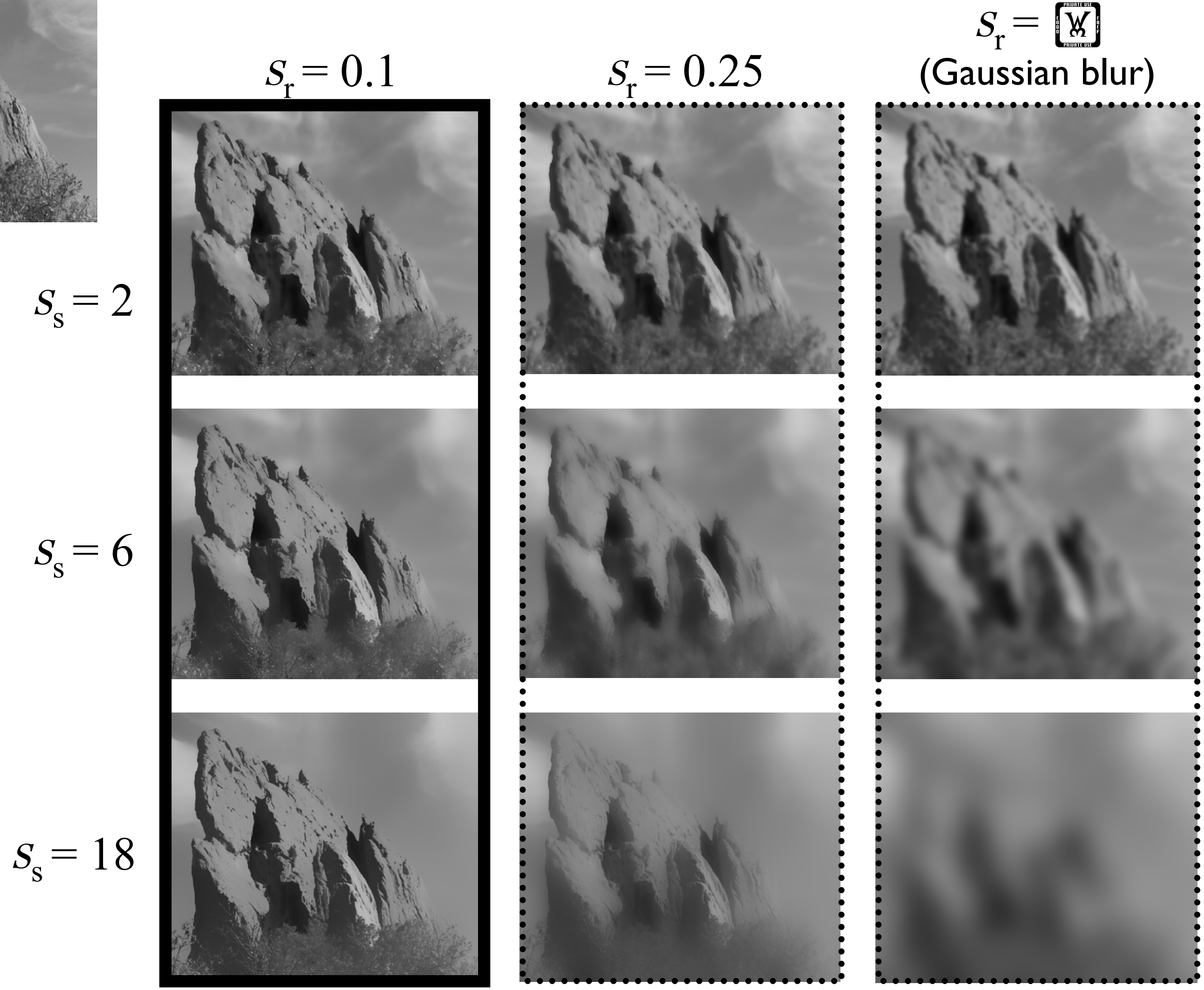

$s_r = 0.1$


$s_r = 0.25$


$S_r =$
(Gaussian blur)

Varying the Space Parameter

input




input


$S_s = 2$


$S_s = 6$


$S_s = 18$

How to Set the Parameters

Depends on the application. For instance:

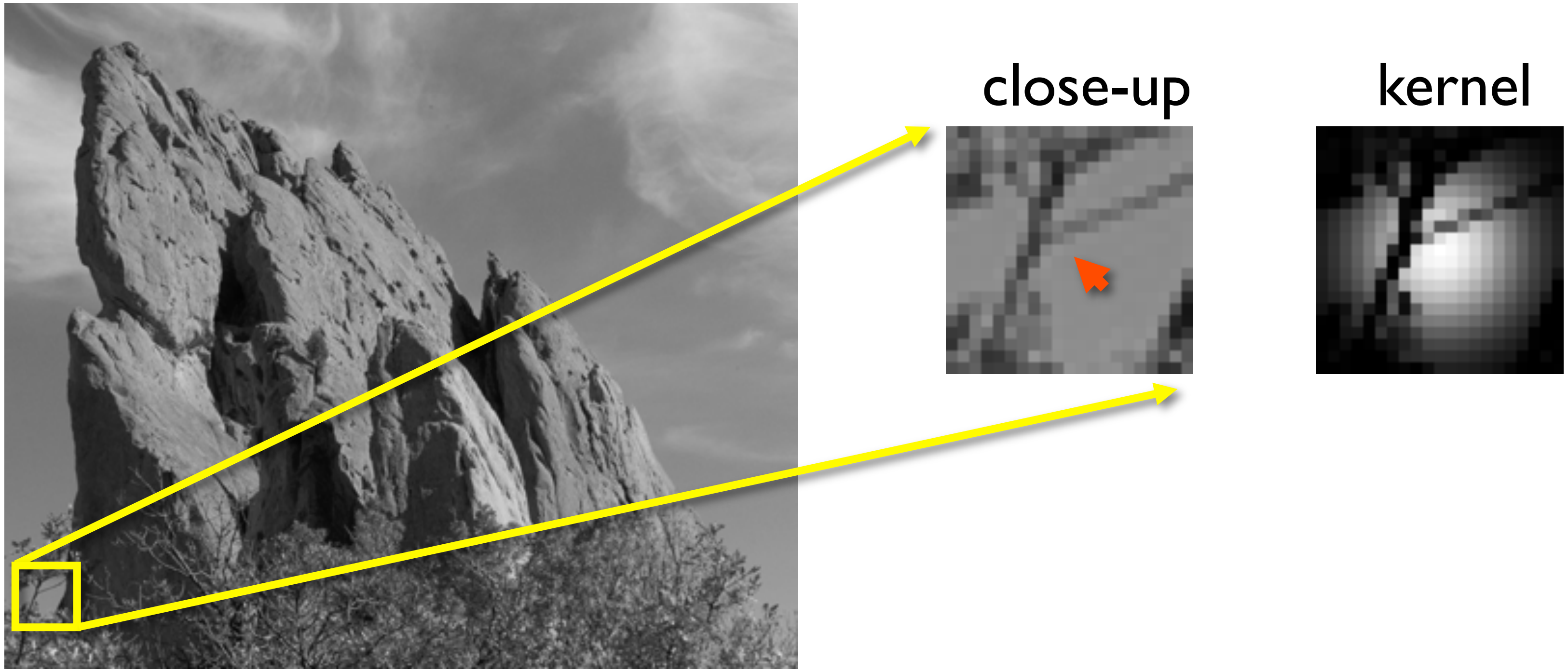
- space parameter: proportional to image size
  - e.g., 2% of image diagonal

- range parameter: proportional to edge amplitude
  - e.g., mean or median of image gradients

- independent of resolution and exposure

Bilateral Filter Crosses Thin Lines

- Bilateral filter averages across
  features thinner than $\sim 2s_s$
- Desirable for smoothing: more pixels = more robust
- Different from diffusion that stops at thin lines



Iterating the Bilateral Filter

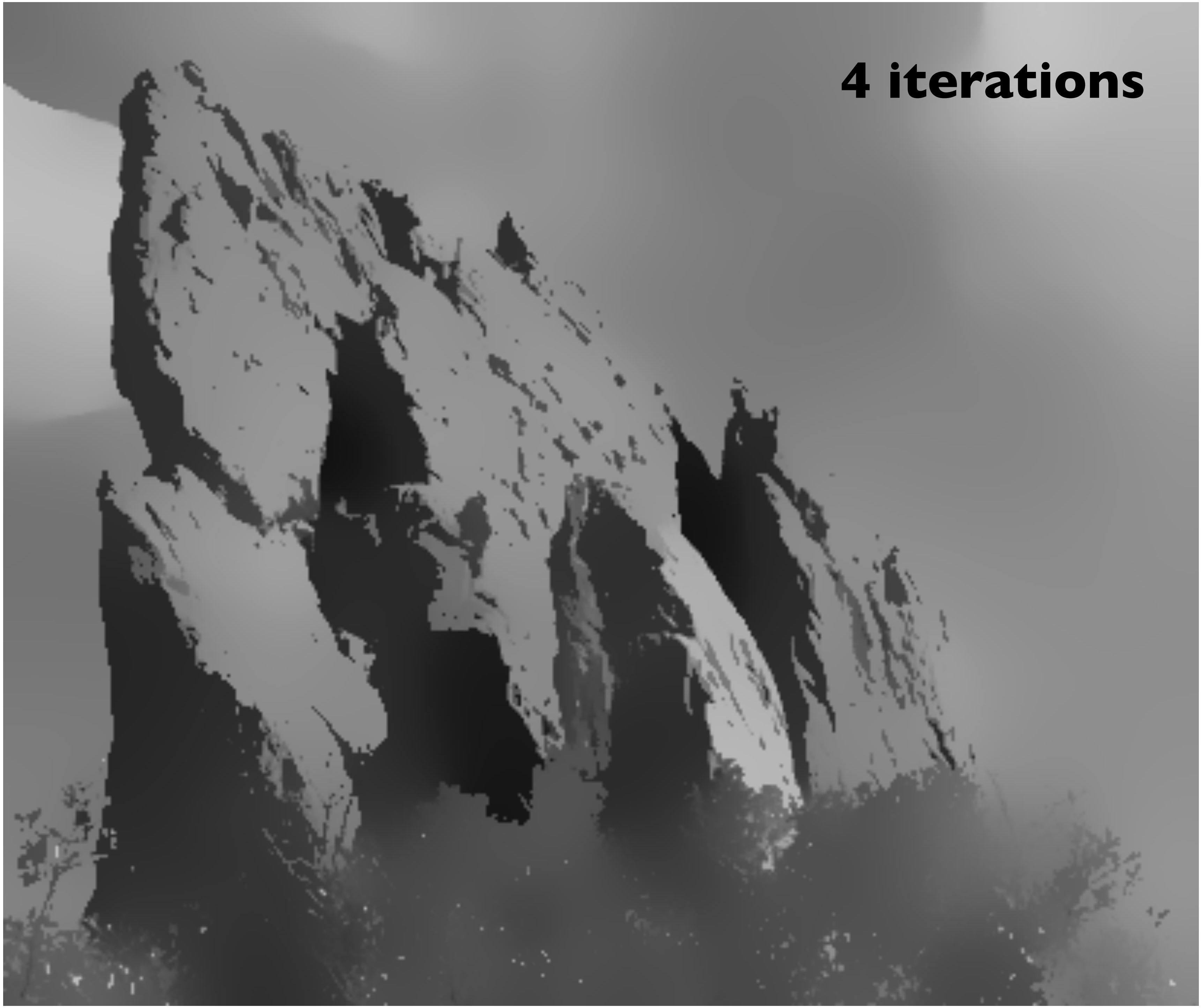
$$I_{(n+1)} = BF\left[I_{(n)}\right]$$

- Generate more piecewise-flat images
- Often not needed in computational photo.


input


1 iteration


2 iterations


4 iterations

Bilateral Filtering Color Images

For gray-level images

intensity difference

$$BF[I]_{\mathbf{p}} = \frac{1}{W_{\mathbf{p}}} \sum_{\mathbf{q} \in S} G_{\sigma_s}(\| \mathbf{p} - \mathbf{q} \|) \, G_{\sigma_r}\left(\boxed{| I_{\mathbf{p}} - I_{\mathbf{q}} |} \right) \boxed{I_{\mathbf{q}}}$$

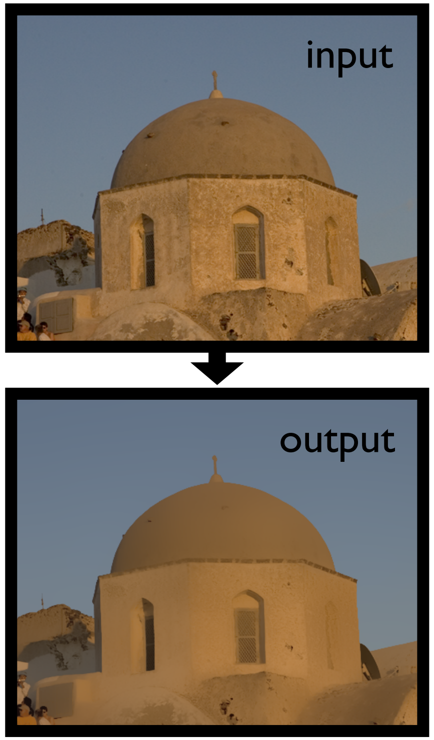
scalar

For color images

color difference

$$BF[I]_{\mathbf{p}} = \frac{1}{W_{\mathbf{p}}} \sum_{\mathbf{q} \in S} G_{\sigma_s}(\| \mathbf{p} - \mathbf{q} \|) \, G_{\sigma_r}\left(\boxed{\| \mathbf{C}_{\mathbf{p}} - \mathbf{C}_{\mathbf{q}} \|} \right) \boxed{\mathbf{C}_{\mathbf{q}}}$$

3D vector (RGB, Lab)



Hard to Compute

- Nonlinear

$$BF[I]_{\mathbf{p}} = \boxed{\frac{1}{W_{\mathbf{p}}}} \sum_{\mathbf{q} \in S} G_{\sigma_s}(\| \mathbf{p} - \mathbf{q} \|) \boxed{G_{\sigma_r}(| I_{\mathbf{p}} - I_{\mathbf{q}} |)} I_{\mathbf{q}}$$

- Complex, spatially varying kernels
  - Cannot be precomputed, no FFT…

- Brute-force implementation is slow > 10min

Basic denoising

Noisy input

Bilateral filter 7x7 window

Basic denoising

Bilateral filter

Median 3x3

Basic denoising

Bilateral filter

Median 5x5

Basic denoising

Bilateral filter

Bilateral filter – lower sigma

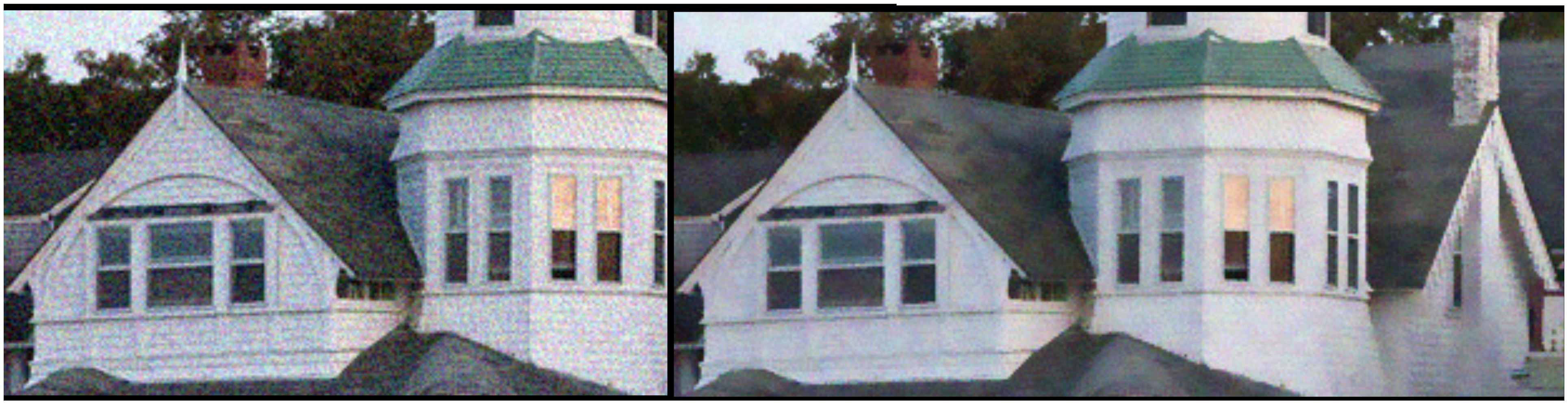
Basic denoising

Bilateral filter

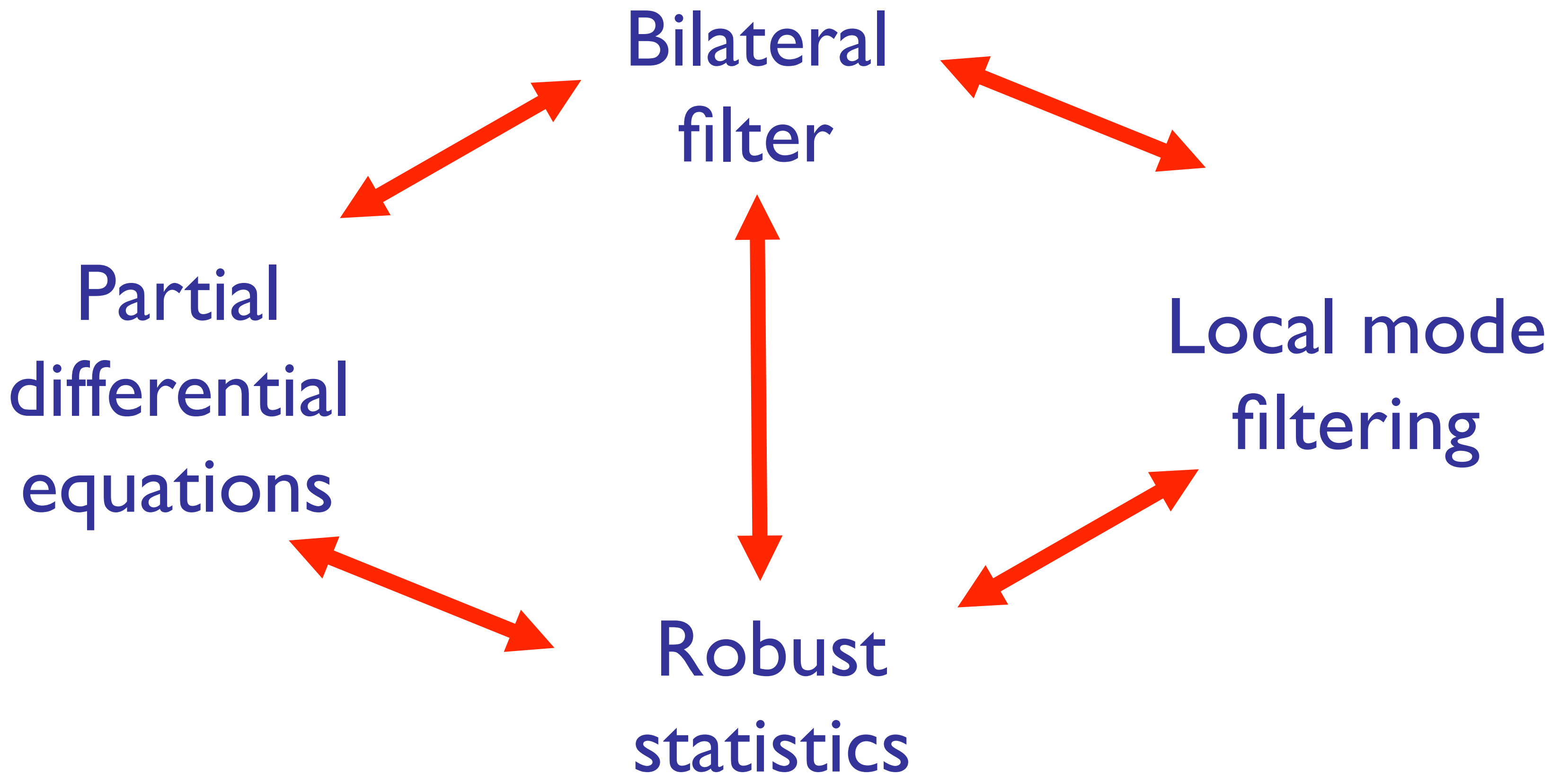
Bilateral filter – higher sigma

Denoising

- Small spatial sigma (e.g. 7x7 window)
- Adapt range sigma to noise level
- Maybe not best denoising method, but best simplicity/quality tradeoff
  – No need for acceleration (small kernel)
  – But the denoising feature in e.g. Photoshop is better



Goal: Understand how does bilateral filter relates with other methods



more in BIL717 Image Processing graduate course..

New Idea:
NL-Means Filter (Buades 2005)

- Same goals: 'Smooth within Similar Regions'

- **KEY INSIGHT**: Generalize, extend'Similarity'
  - **Bilateral:**
    Averages neighbors with **similar intensities**;

  - **NL-Means:**
    Averages neighbors with **similar neighborhoods!**

NL-Means Method: Buades (2005)

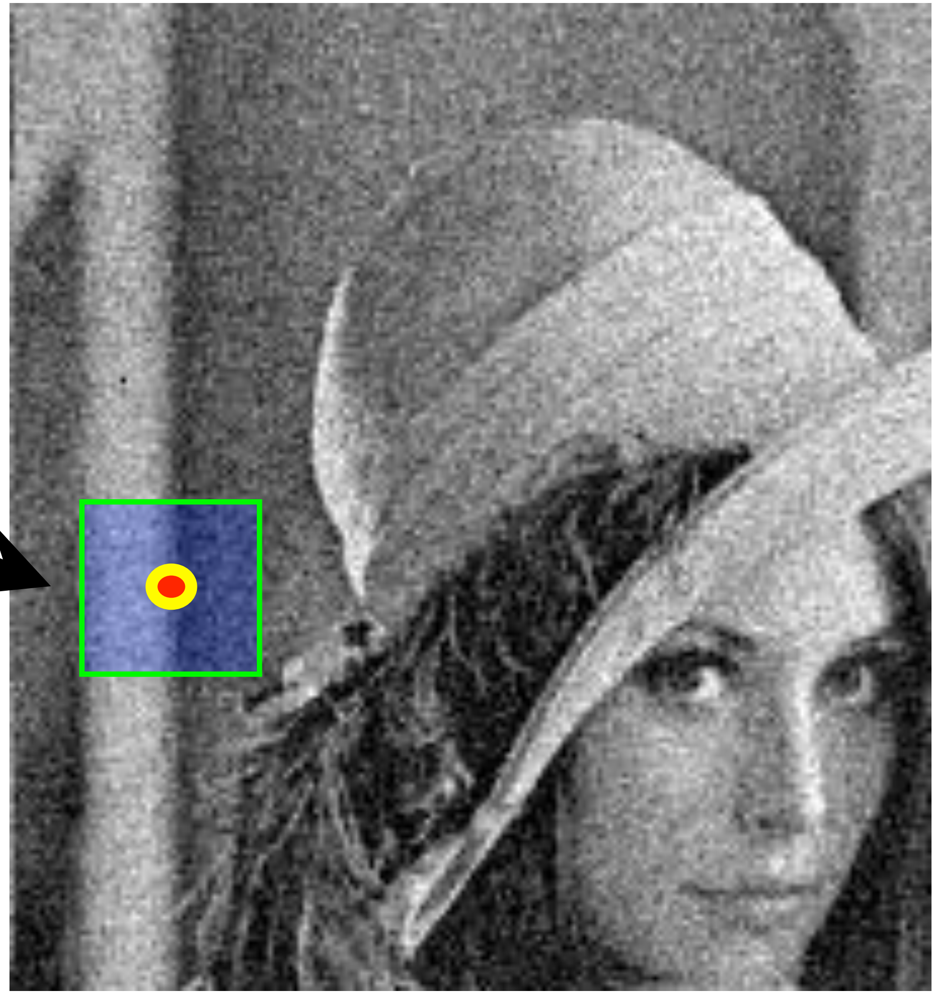
- For each and every pixel **p:**

NL-Means Method: Buades (2005)

- For each and every pixel **p:**
  - Define a small, simple fixed size neighborhood;

NL-Means Method: Buades (2005)

$$\mathbf{V_p} = \begin{bmatrix} 0.74 \\ 0.32 \\ 0.41 \\ 0.55 \\ \cdots \\ \cdots \\ \cdots \end{bmatrix}$$



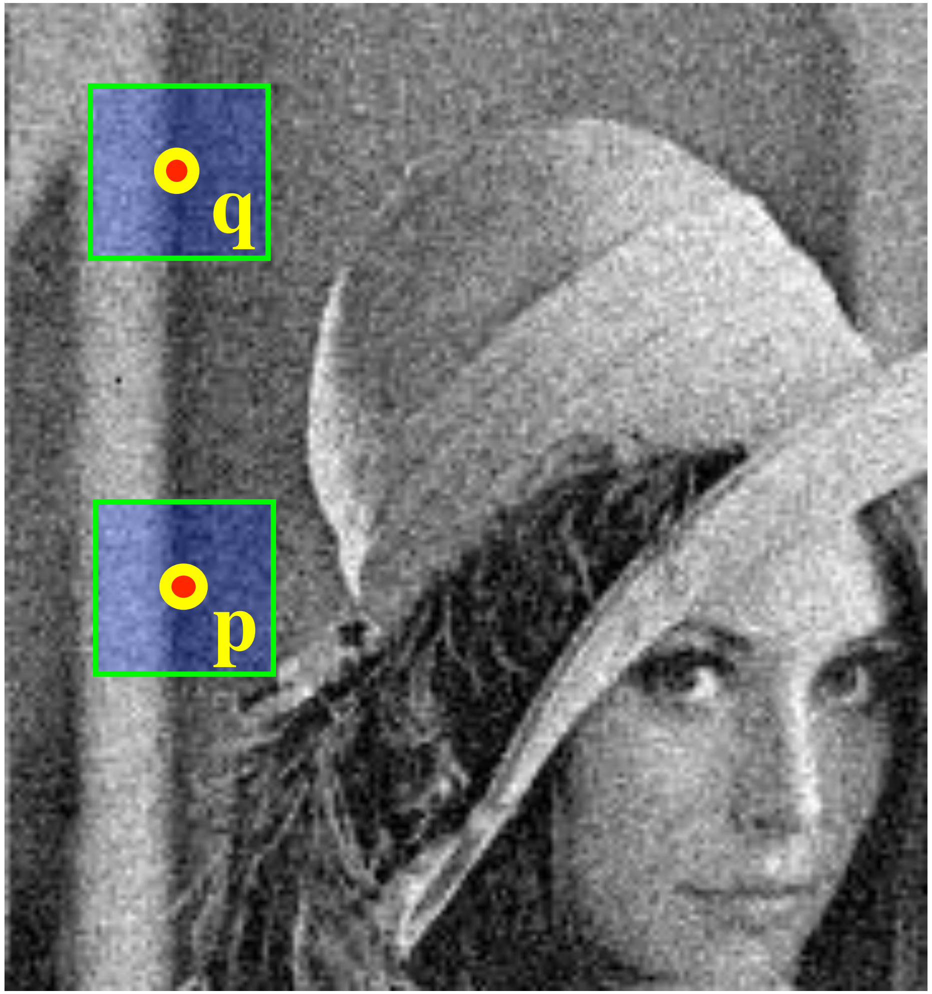
- For each and every pixel **p**:
  - Define a small, simple fixed size neighborhood;
  - Define vector $\mathbf{V_p}$: a list of neighboring pixel values.

NL-Means Method: Buades (2005)

'Similar' pixels **p, q**

→ **SMALL** vector distance;

$$\| V_p - V_q \|^2$$

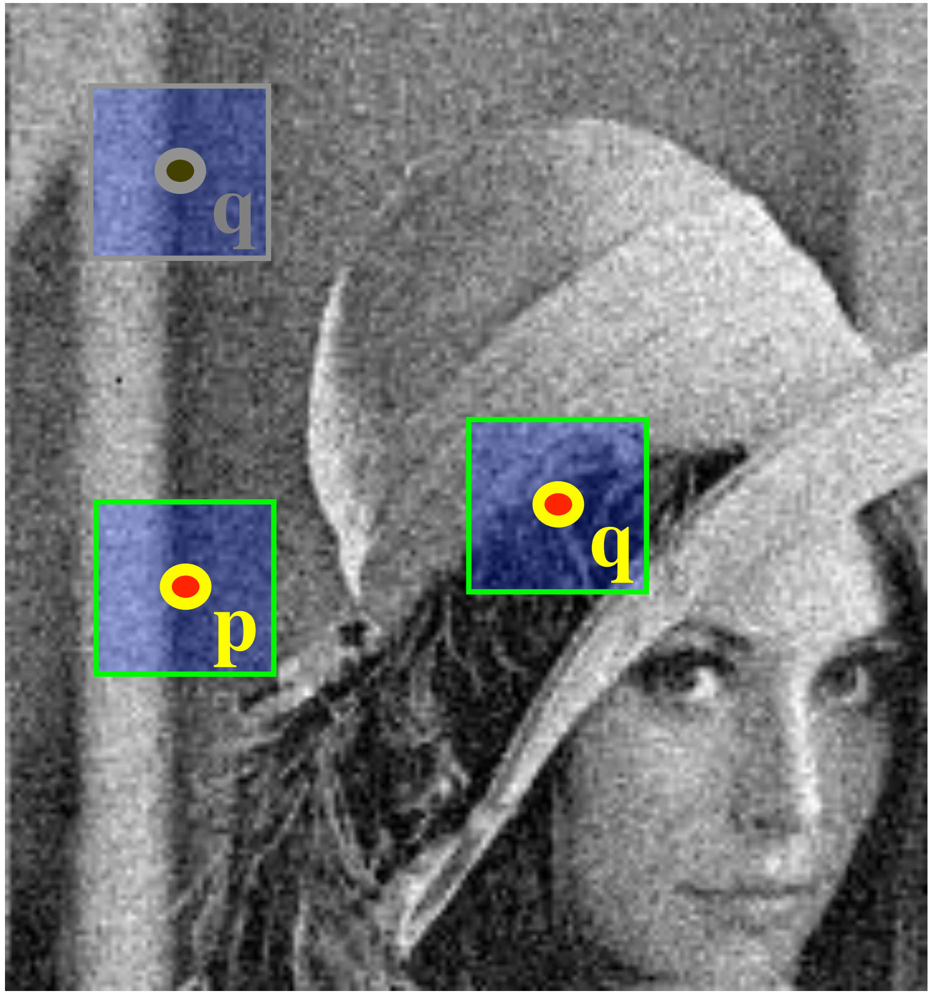


NL-Means Method: Buades (2005)

<u>'Dissimilar'</u> pixels **p, q**

→ **LARGE**
vector distance;

$$\| V_p - V_q \|^2$$



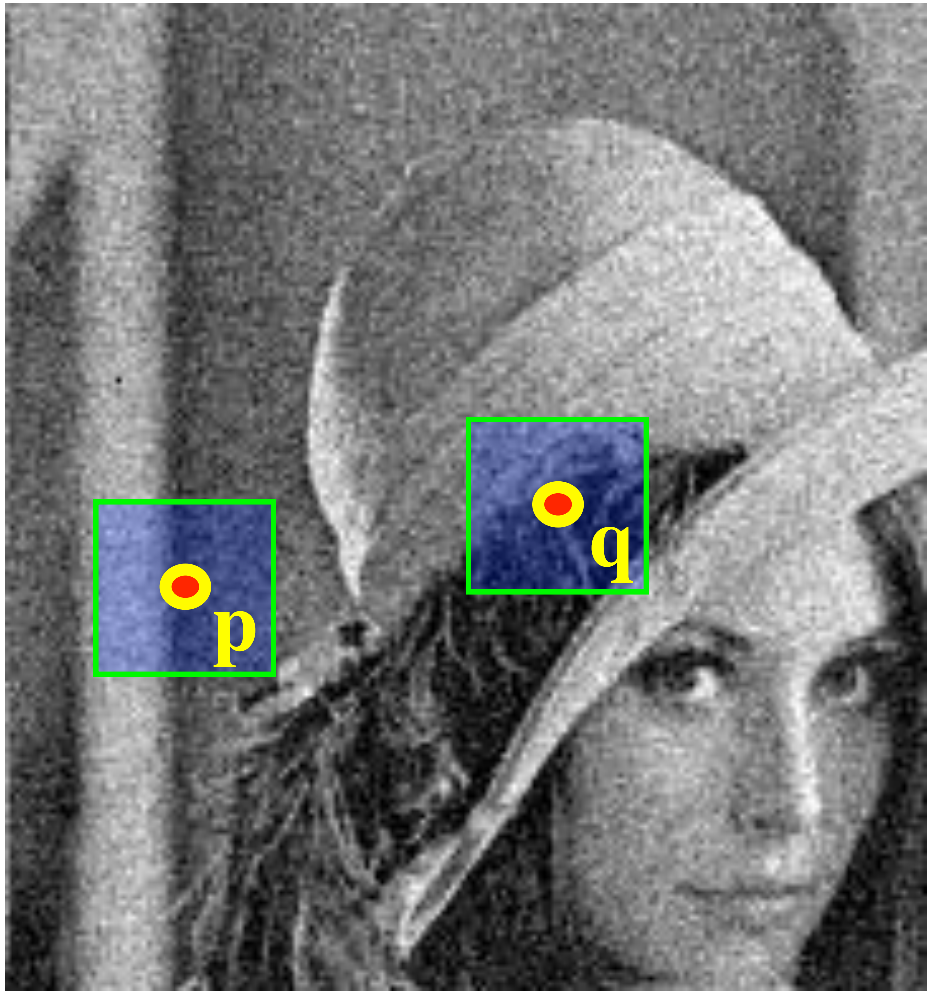
NL-Means Method: Buades (2005)

'Dissimilar' pixels **p, q**

→ **LARGE** vector distance;

$$\boxed{\| V_p - V_q \|^2}$$

Filter with this!



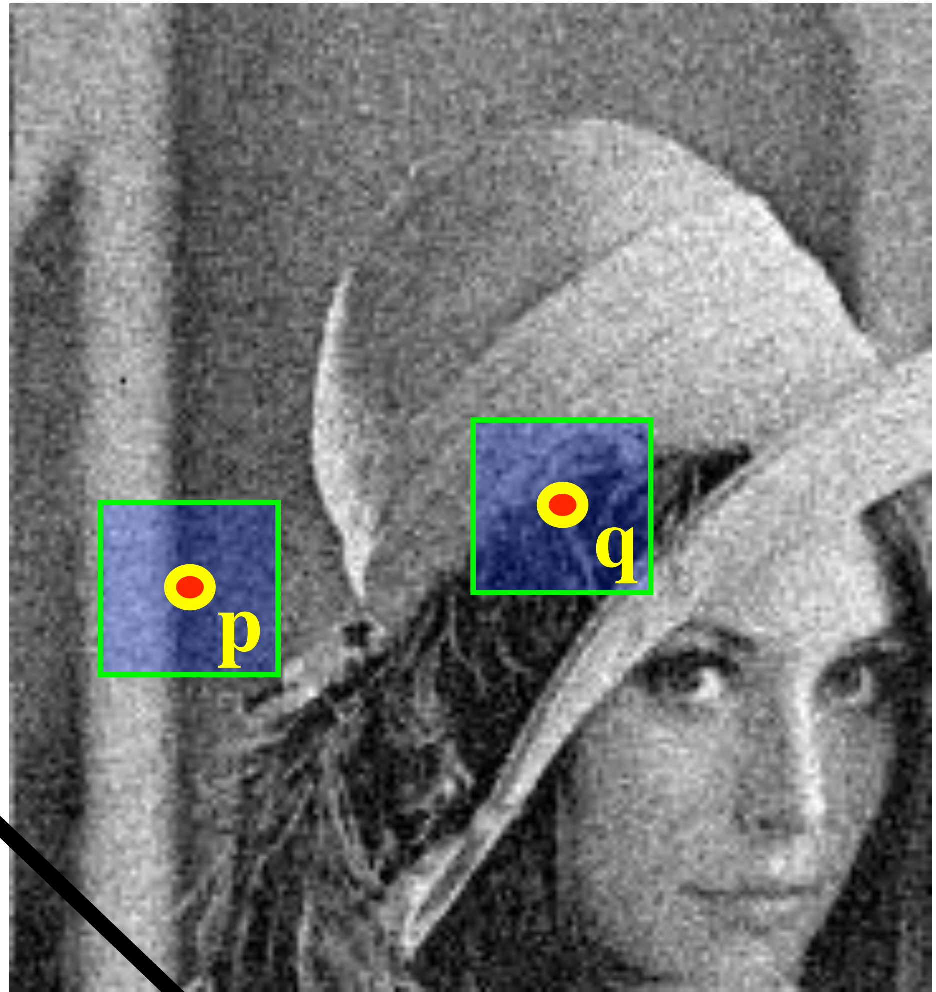
NL-Means Method: Buades (2005)

p, q neighbors define

a vector distance;

Filter with this:

$$\| \mathbf{V_p} - \mathbf{V_q} \|^2$$



No spatial term!

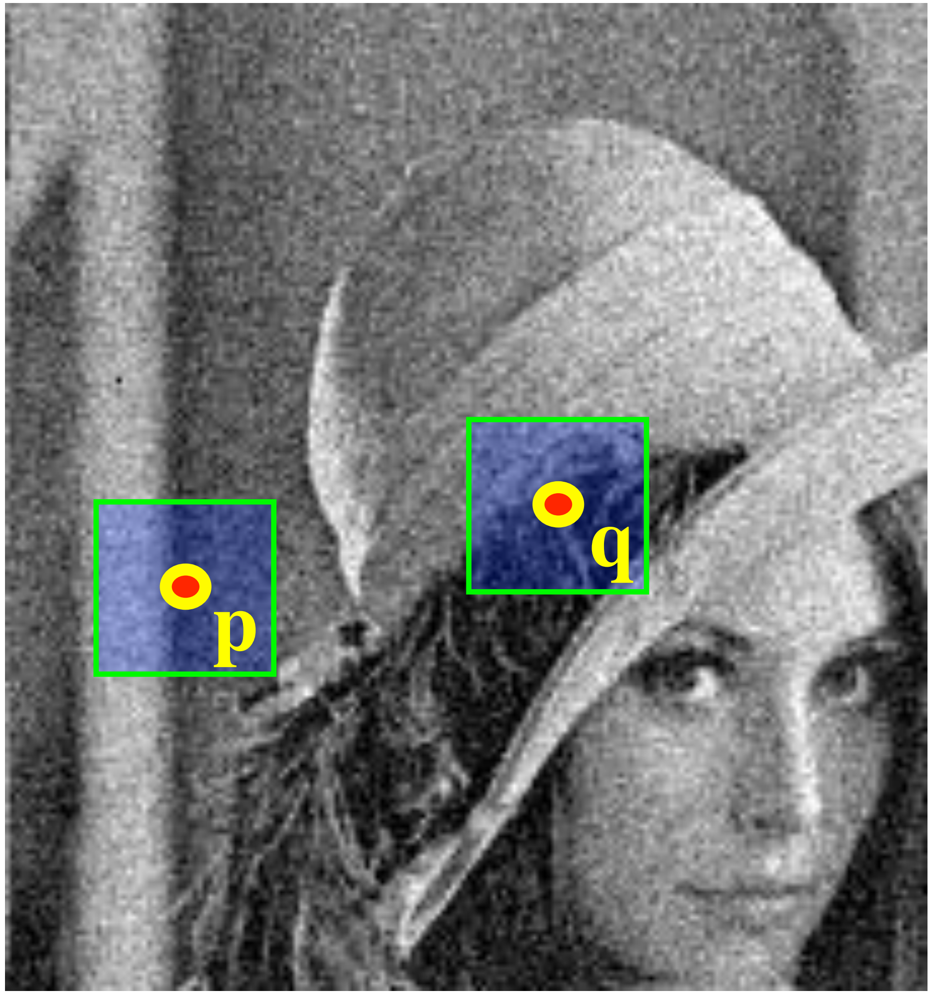
$$NLMF[I]_{\mathbf{p}} = \frac{1}{W_{\mathbf{p}}} \sum_{\mathbf{q} \in S} \cancel{G_{\sigma_s}\left(\| \mathbf{p} - \mathbf{q} \|\right)} \boxed{G_{\sigma_r}\left(\boxed{\| \vec{V}_{\mathbf{p}} - \vec{V}_{\mathbf{q}} \|^2}\right)} I_{\mathbf{q}}$$

NL-Means Method: Buades (2005)

pixels **p, q** neighbors
Set a vector distance;

$$\boxed{\| \mathbf{V}_\mathbf{p} - \mathbf{V}_\mathbf{q} \|^2}$$

Vector Distance to p sets weight for each pixel q



$$NLMF[I]_\mathbf{p} = \frac{1}{W_\mathbf{p}} \sum_{\mathbf{q} \in S} \boxed{G_{\sigma_\mathrm{r}}\left(\| \vec{V}_\mathbf{p} - \vec{V}_\mathbf{q} \|^2\right)} I_\mathbf{q}$$

NL-Means Filter (Buades 2005)

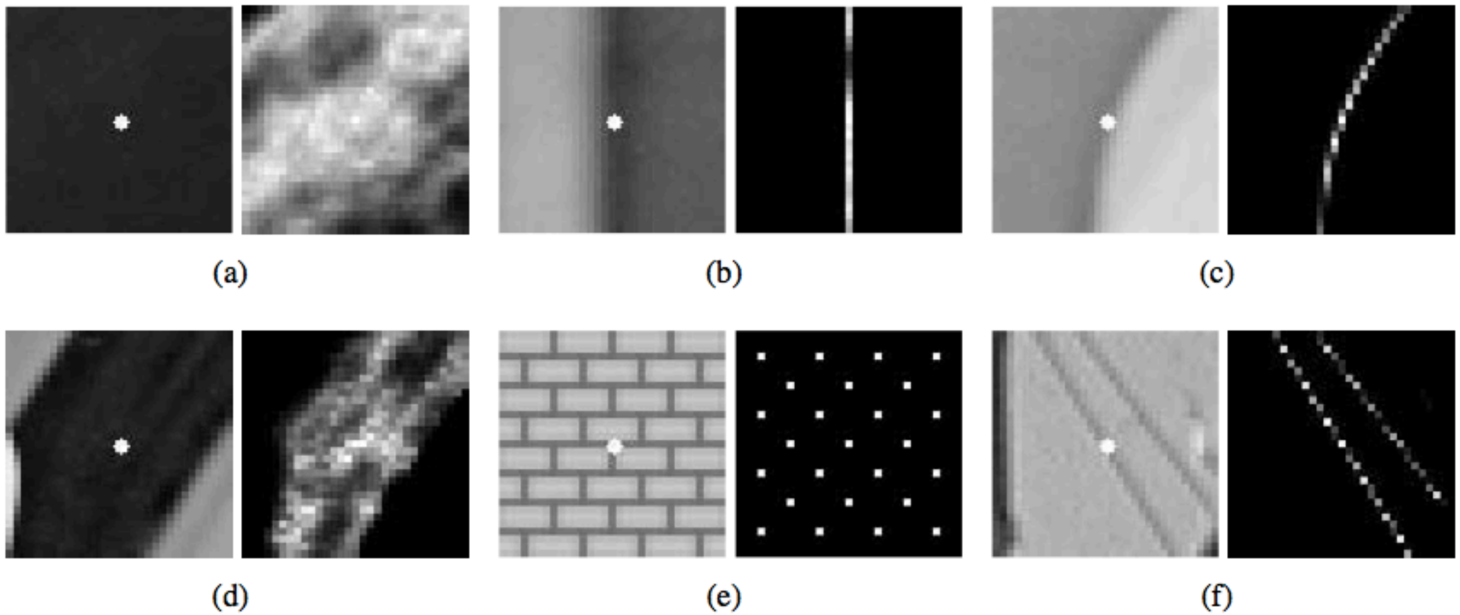


Figure 2. Display of the NL-means weight distribution used to estimate the central pixel of every image. The weights go from 1(white) to zero(black).

NL-Means Filter (Buades 2005)

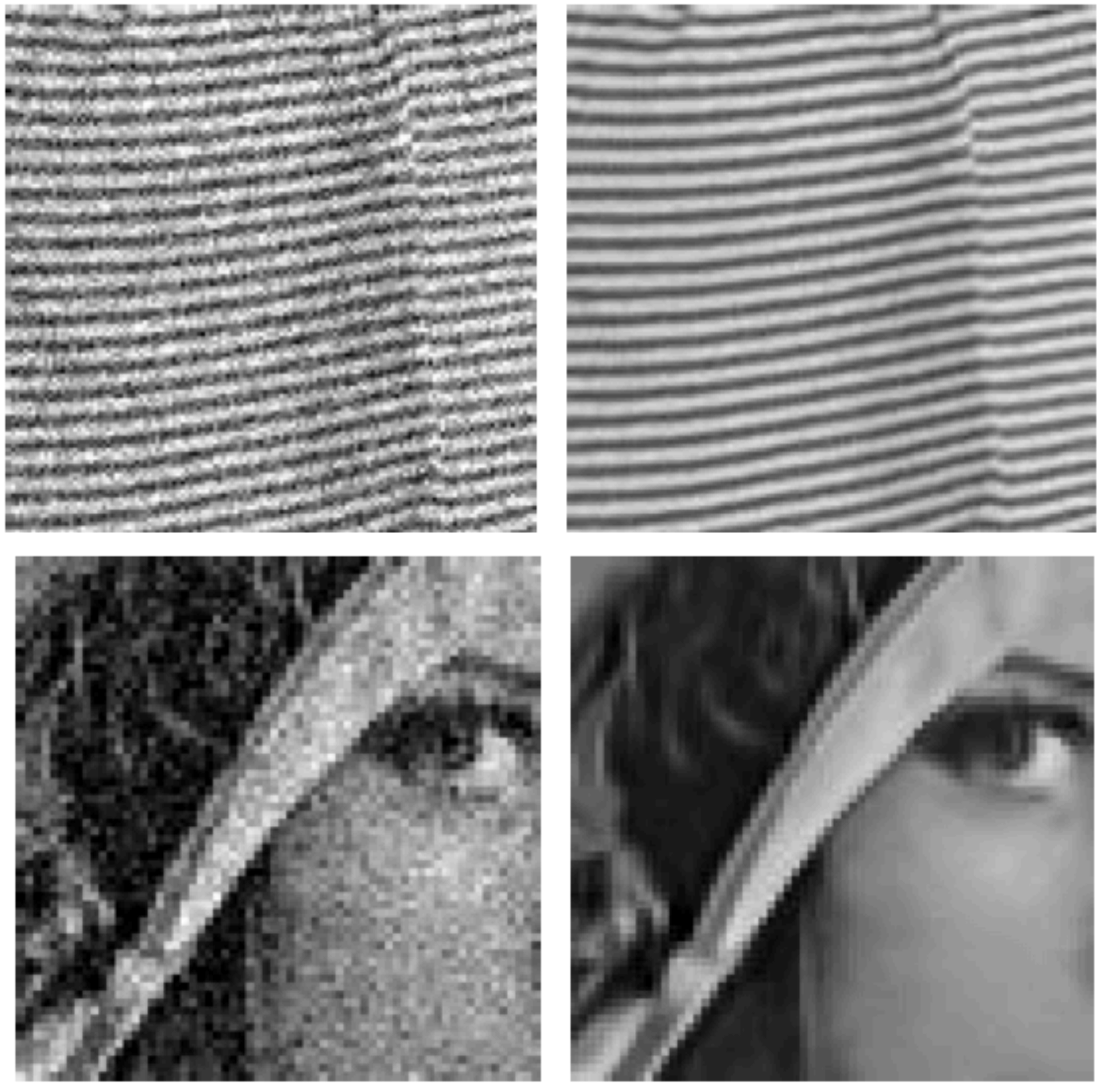


FIG. 9. *NL-means denoising experiment with a natural image. Left: Noisy image with standard deviation* 20. *Right: Restored image.*

NL-Means Filter (Buades 2005)

- Noisy source image:

NL-Means Filter (Buades 2005)

- Gaussian Filter

Low noise,

Low detail

NL-Means Filter (Buades 2005)

- Anisotropic Diffusion

(Note 'stairsteps': ~ piecewise constant)

NL-Means Filter (Buades 2005)

- Bilateral Filter

(better, but similar 'stairsteps':

NL-Means Filter (Buades 2005)

- NL-Means:

Sharp,

Low noise,

Few artifacts.

NL-Means Filter (Buades 2005)

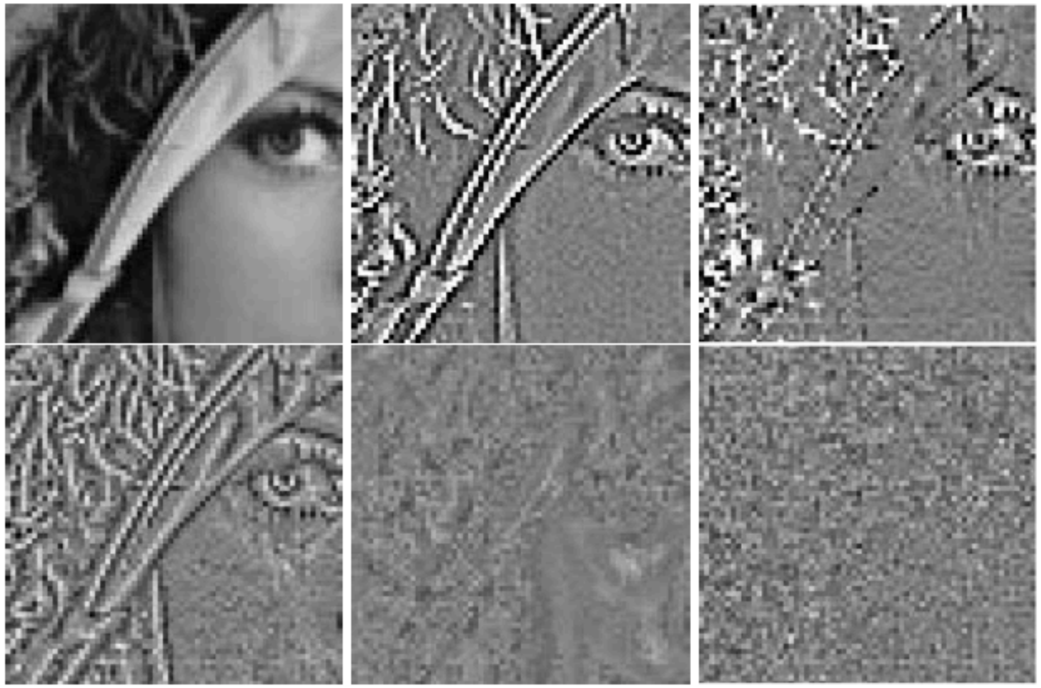


Figure 4. Method noise experience on a natural image. Displaying of the image difference $u - D_h(u)$. From left to right and from top to bottom: original image, Gauss filtering, anisotropic filtering, Total variation minimization, Neighborhood filtering and NL-means algorithm. The visual experiments corroborate the formulas of section 2.

NL-Means Filter (Buades 2005)

http://www.ipol.im/pub/algo/bcm_non_local_means_denoising/

NL-Means Filter (Buades 2005)

original

http://www.ipol.im/pub/algo/bcm_non_local_means_denoising/

NL-Means Filter (Buades 2005)

noisy

http://www.ipol.im/pub/algo/bcm_non_local_means_denoising/

NL-Means Filter (Buades 2005)

denoised

http://www.ipol.im/pub/algo/bcm_non_local_means_denoising/

NL-Means Filter (Buades 2005)

original

http://www.ipol.im/pub/algo/bcm_non_local_means_denoising/

NL-Means Filter (Buades 2005)

noisy

http://www.ipol.im/pub/algo/bcm_non_local_means_denoising/

NL-Means Filter (Buades 2005)

denoised

http://www.ipol.im/pub/algo/bcm_non_local_means_denoising/