THE UNIVERSITY OF TEXAS AT DALLAS

Image Processing: Filtering II

CS 6384 Computer Vision

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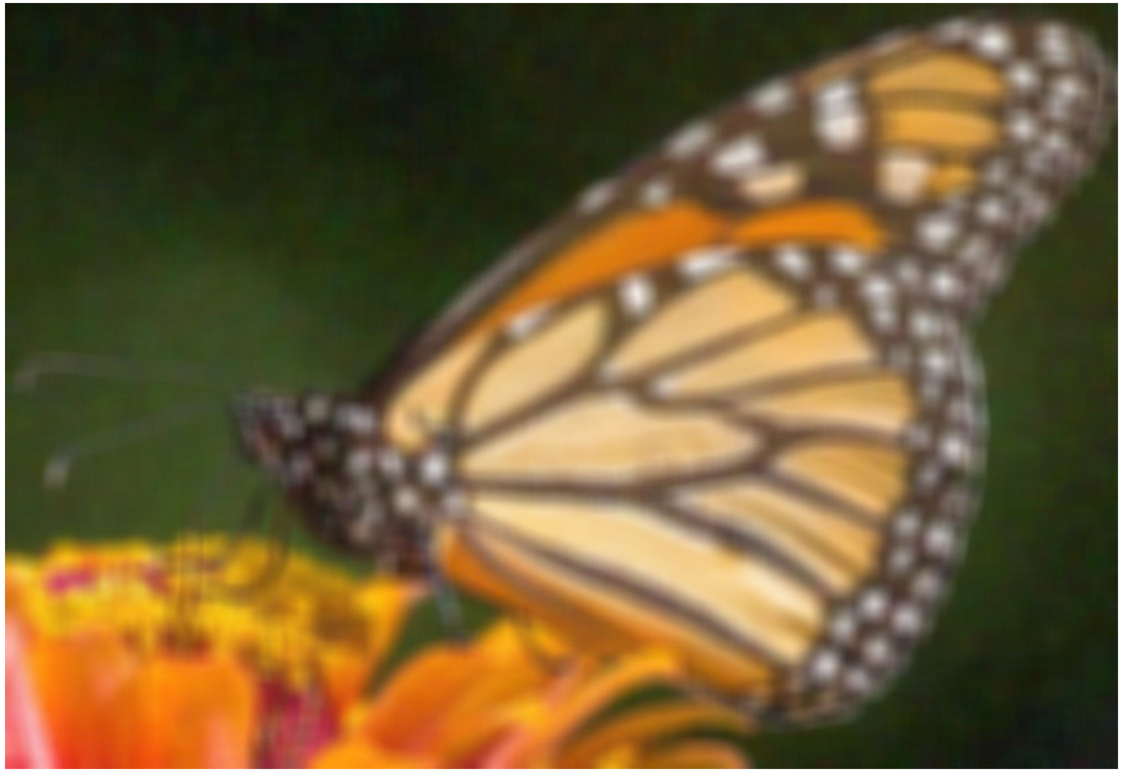
Department of Computer Science

Many slides in this lecture were inspired or adapted from Ioannis (Yannis) Gkioulekas.

Filtered Image (Gaussian)

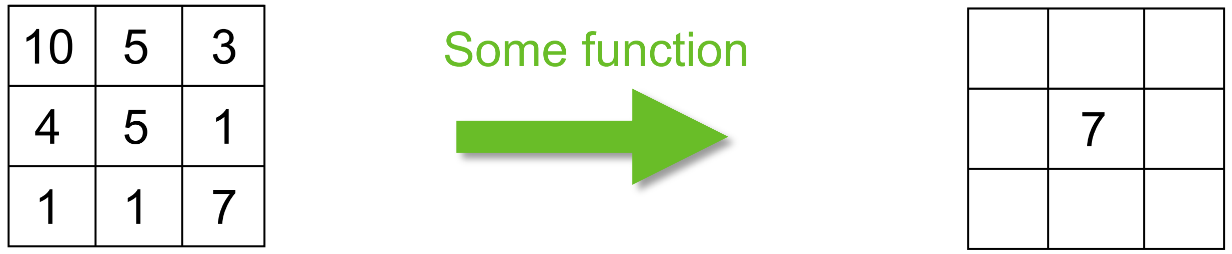


Noisy Image

Question: How to handle blurry artifacts and preserve image edges in the filtered image?

Recap: Image Filtering

Modify the pixels in an image based on some function of a local neighborhood of each pixel



Local image data

Modified image data

Let f be the image, w be the $(2n+1)\times(2n+1)$ kernel weights and h be the filtered output image

$$h[u,v] = \sum_{k=-n}^{n} \sum_{l=-n}^{n} w[k,l] f[u+k, v+l]$$

cross-correlation == convolution, when the kernel is isotropic

Recap: Image Filtering Process

1/9	1/9	1/9
1/9	1/9	1/9
1/9	1/9	1/9

kernel

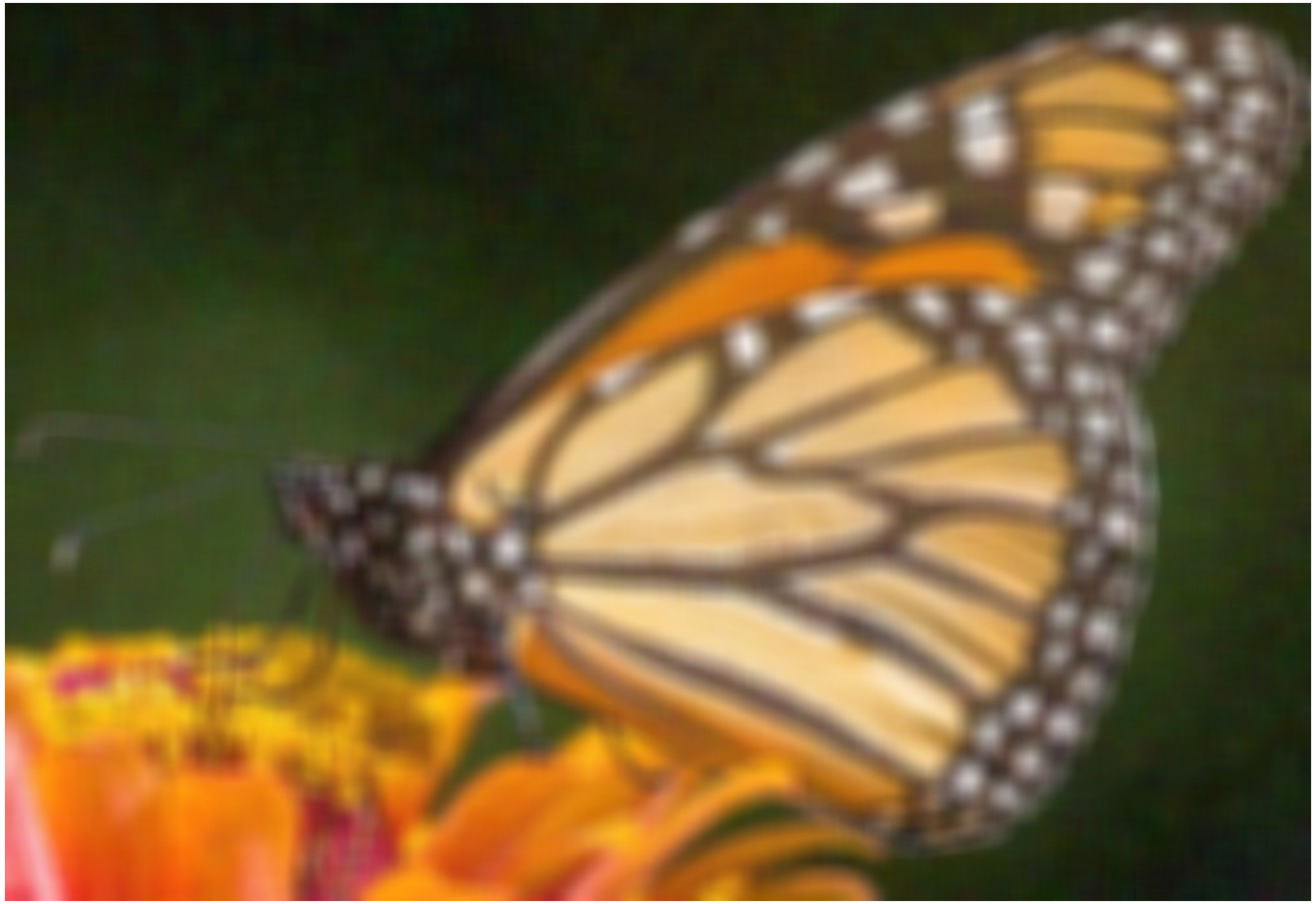
Noisy Image

Apply the filter to every pixel

Recap: Image Filtering Process

1/9	1/9	1/9
1/9	1/9	1/9
1/9	1/9	1/9

kernel

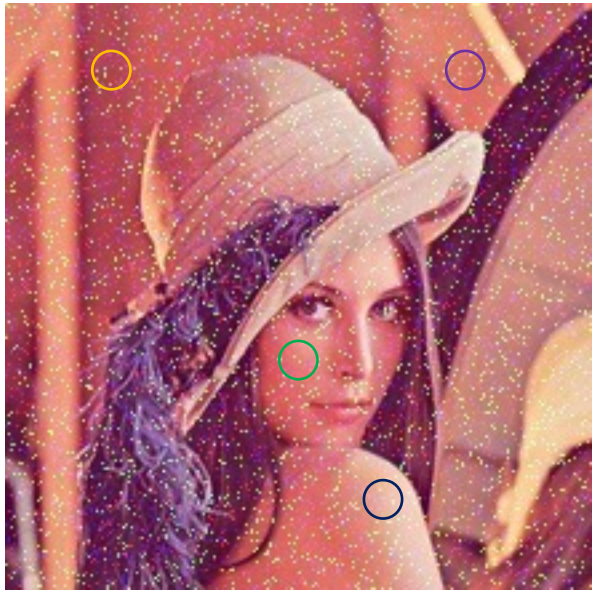


Filtered Image

Apply the filter to every pixel

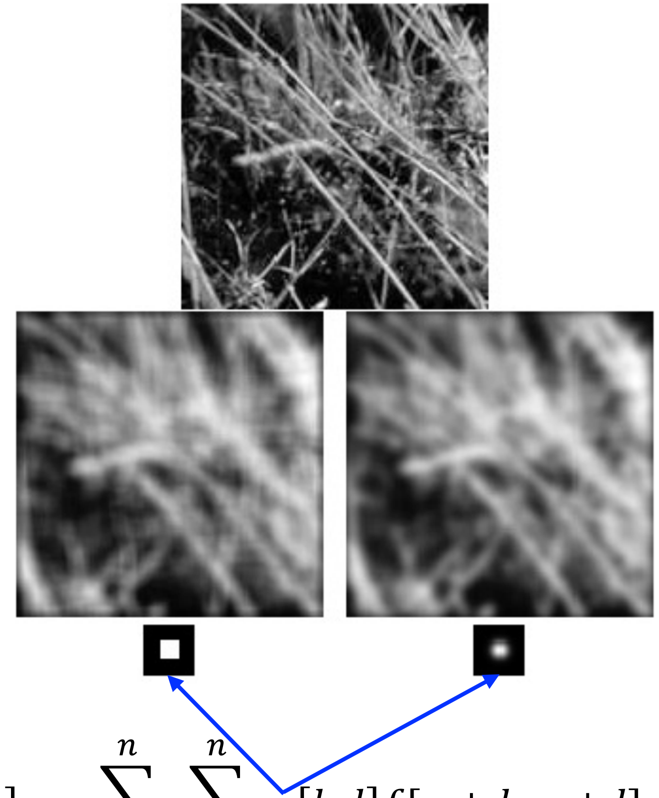
Recap: Image Prior: Local Smoothness

- Local natural image regions are typically smooth or uniform
- The overall structures or texture of a natural image often has a more subtle and gradual variation than image noise



- Image pixels in a small window (e.g., 5x5) usually are similar
- Noise values are dramatically changing at arbitrary directions
- Due to noises, a noisy image have higher local variations than the clean image

Recap: Local Smoothness with Mean vs Gaussian filtering



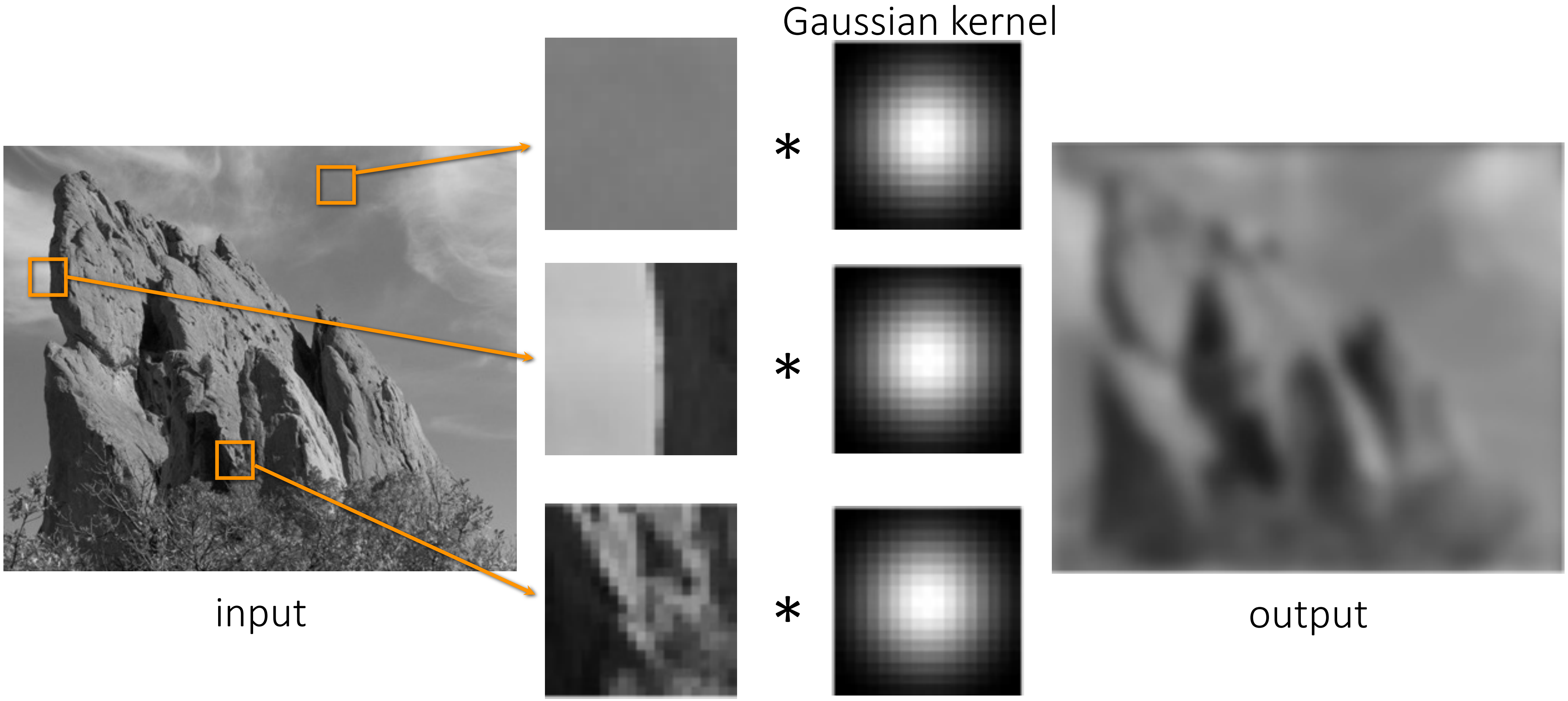
$$h[u,v] = \sum_{k=-n}^{n} \sum_{l=-n}^{n} w[k,l] f[u+k, v+l]$$

Both mean and Gaussian utilize local smoothness prior

- Mean filter assumes all pixels in a local window are equally important
- Gaussian filter assumes pixels that are closer to the target pixel are more important

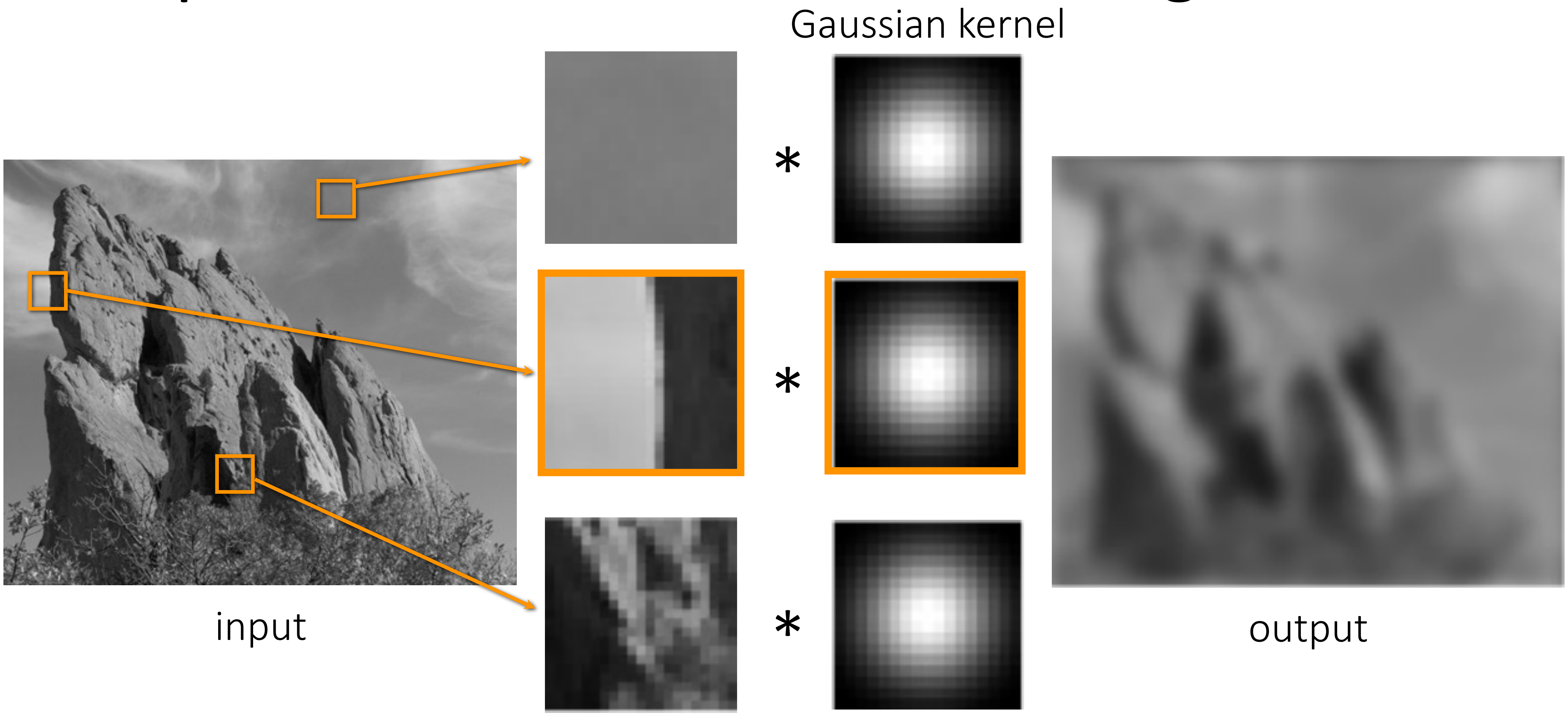
We need to design a better kernel w for improving filtering results.

The problem with Gaussian filtering



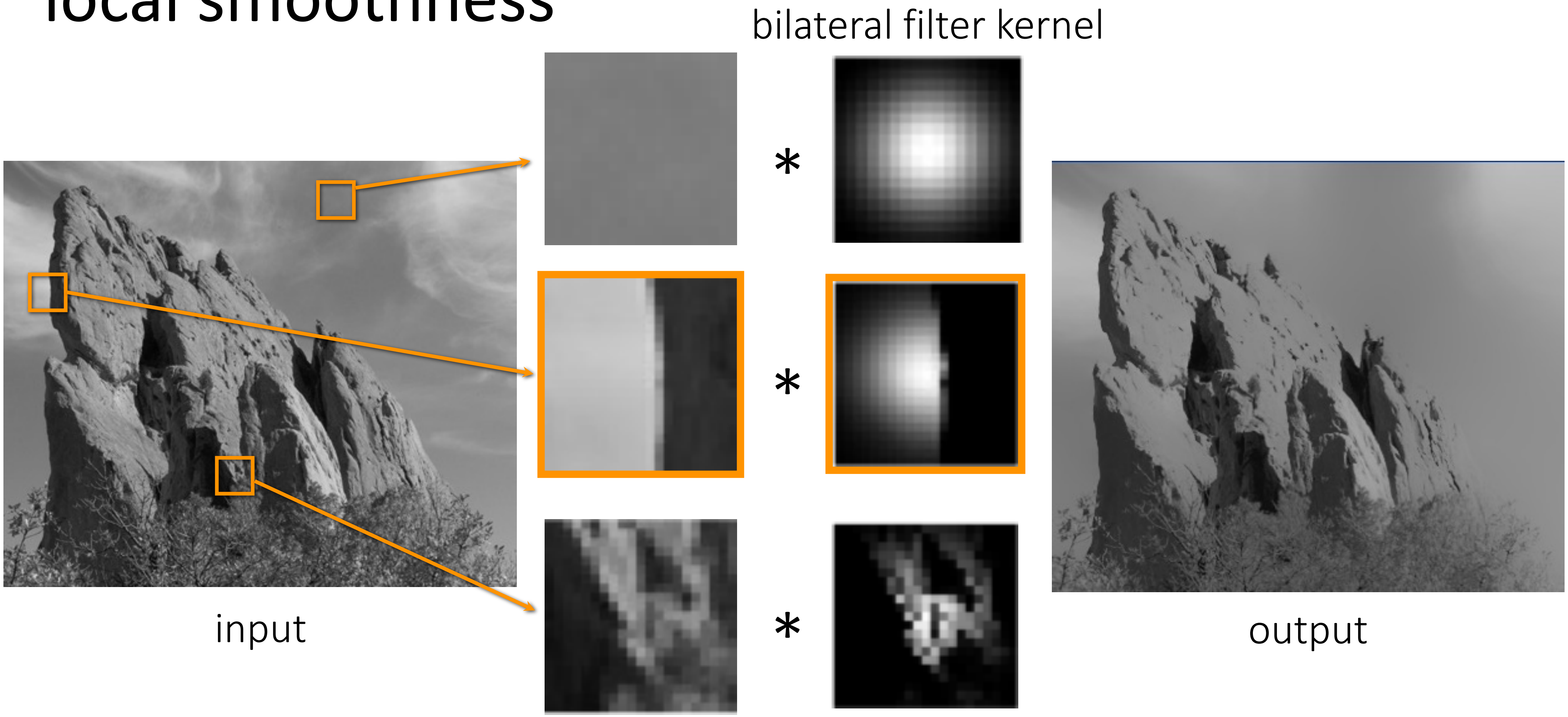
Why is the output so blurry?

The problem with Gaussian filtering



Blur kernel averages across edges

The bilateral filtering solution: Edge-preserving local smoothness



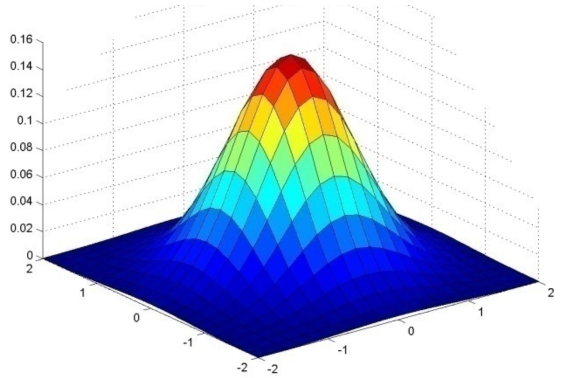
Do not blur if there is an edge! How does it do that?

Bilateral filtering

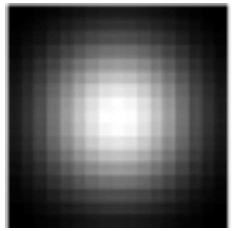
$$h[m,n] = \frac{1}{W_{mn}} \sum_{k,l} g[k,l] r_{mn}[k,l] f[m+k, n+l]$$

Bilateral filtering

$$h[m,n] = \frac{1}{W_{mn}} \sum_{k,l} g[k,l] r_{mn}[k,l] f[m+k, n+l]$$



Spatial weighting



$$g[k,l] = \frac{1}{2\pi{\sigma_s}^2} \exp(-\frac{(k^2 + l^2)}{2{\sigma_s}^2})$$

σ_s

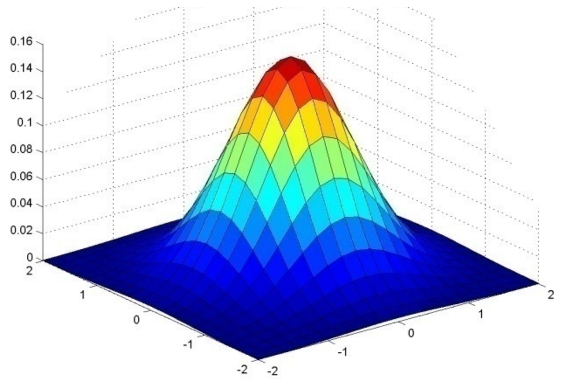
Assign a pixel a large weight if: 1) it's nearby

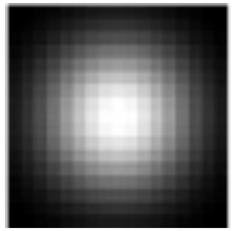
Bilateral filtering

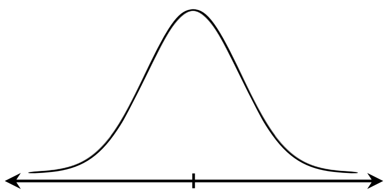
$$h[m,n] = \frac{1}{W_{mn}} \sum_{k,l} g[k,l]\, r_{mn}[k,l]\, f[m+k, n+l]$$

Spatial weighting

Intensity range weighting







$$r_{mn} = \frac{1}{\sqrt{2\pi}\sigma_r} e^{-\frac{x^2}{2\sigma_r^2}}$$

$$x = f[m,n] - f[m+k, n+l]$$

$$g[k,l] = \frac{1}{2\pi\sigma_s^2} \exp\left(-\frac{(k^2 + l^2)}{2\sigma_s^2}\right)$$

σ_s σ_r

Assign a pixel a large weight if: 1) it's nearby and 2) it looks like me

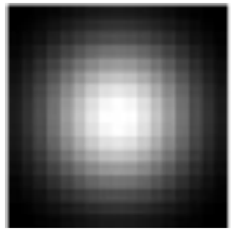
Bilateral filtering

$$h[m,n] = \frac{1}{W_{mn}} \sum_{k,l} g[k,l] r_{mn}[k,l] f[m+k, n+l]$$

Normalization factor

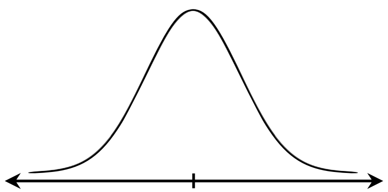
$$W_{mn} = \sum_{k,l} g[k,l] r_{mn}[k,l]$$

Spatial weighting



σ_s

Intensity range weighting



$x = f[m,n] - f[m+k, n+l]$

σ_r

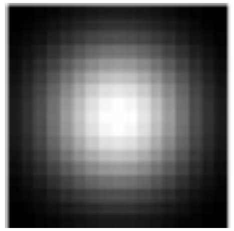
Assign a pixel a large weight if: 1) it's nearby and 2) it looks like me

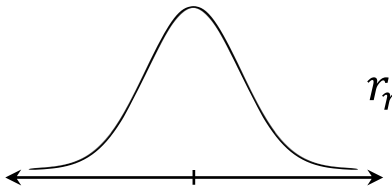
Implementation: Bilateral filtering

$$h[m,n] = \frac{1}{W_{mn}} \sum_{k,l} g[k,l]\, r_{mn}[k,l]\, f[m+k, n+l]$$

Normalization factor | Spatial weighting | Intensity range weighting

$$W_{mn} = \sum_{k,l} g[k,l]\, r_{mn}[k,l]$$





$$r_{mn} = \frac{\cancel{1}}{\cancel{\sqrt{2\pi\sigma_r}}} e^{-\frac{x^2}{2{\sigma_r}^2}}$$

$$x = f[m,n] - f[m+k, n+l]$$

$$g[k,l] = \frac{\cancel{1}}{\cancel{2\pi{\sigma_s}^2}} \exp\left(-\frac{(k^2 + l^2)}{2{\sigma_s}^2}\right)$$

σ_s σ_r

Bilateral filtering vs Gaussian filtering

Which is which?

$$h[m,n] = \sum_{k,l} g[k,l] f[m+k, n+l]$$

$$h[m,n] = \frac{1}{W_{mn}} \sum_{k,l} g[k,l] r_{mn}[k,l] f[m+k, n+l]$$

Bilateral filtering vs Gaussian filtering

Gaussian filtering

$$h[m,n] = \sum_{k,l} g[k,l] f[m+k, n+l]$$

Bilateral filtering

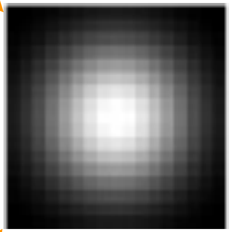
$$h[m,n] = \frac{1}{W_{mn}} \sum_{k,l} g[k,l] r_{mn}[k,l] f[m+k, n+l]$$

Bilateral filtering vs Gaussian filtering

Gaussian filtering

$$h[m,n] = \sum_{k,l} g[k,l] f[m+k, n+l]$$

σ_s



Spatial weighting: favor *nearby* pixels

Bilateral filtering

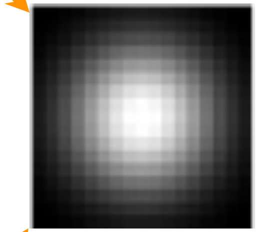
$$h[m,n] = \frac{1}{W_{mn}} \sum_{k,l} g[k,l] r_{mn}[k,l] f[m+k, n+l]$$

Bilateral filtering vs Gaussian filtering

Gaussian filtering

$$h[m,n] = \sum_{k,l} g[k,l] f[m+k, n+l]$$

σ_s

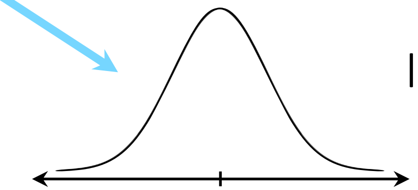


Spatial weighting: favor *nearby* pixels

Bilateral filtering

$$h[m,n] = \frac{1}{W_{mn}} \sum_{k,l} g[k,l] r_{mn}[k,l] f[m+k, n+l]$$

σ_r



$x = f[m,n] - f[m+k, n+l]$

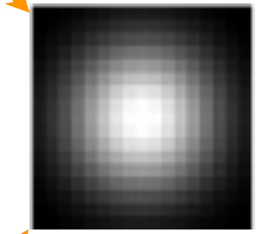
Intensity range weighting: favor *similar* pixels

Bilateral filtering vs Gaussian filtering

Gaussian filtering

$$h[m,n] = \sum_{k,l} g[k,l] f[m+k, n+l]$$

σ_s



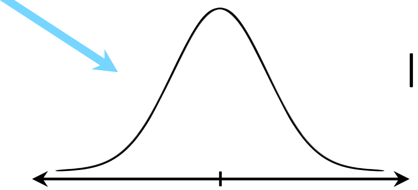
Spatial weighting: favor *nearby* pixels

Bilateral filtering

$$h[m,n] = \frac{1}{W_{mn}} \sum_{k,l} g[k,l] r_{mn}[k,l] f[m+k, n+l]$$

Normalization factor

σ_r



$x = f[m,n] - f[m+k, n+l]$

Intensity range weighting: favor *similar* pixels

Bilateral filtering vs Gaussian filtering

Gaussian filtering

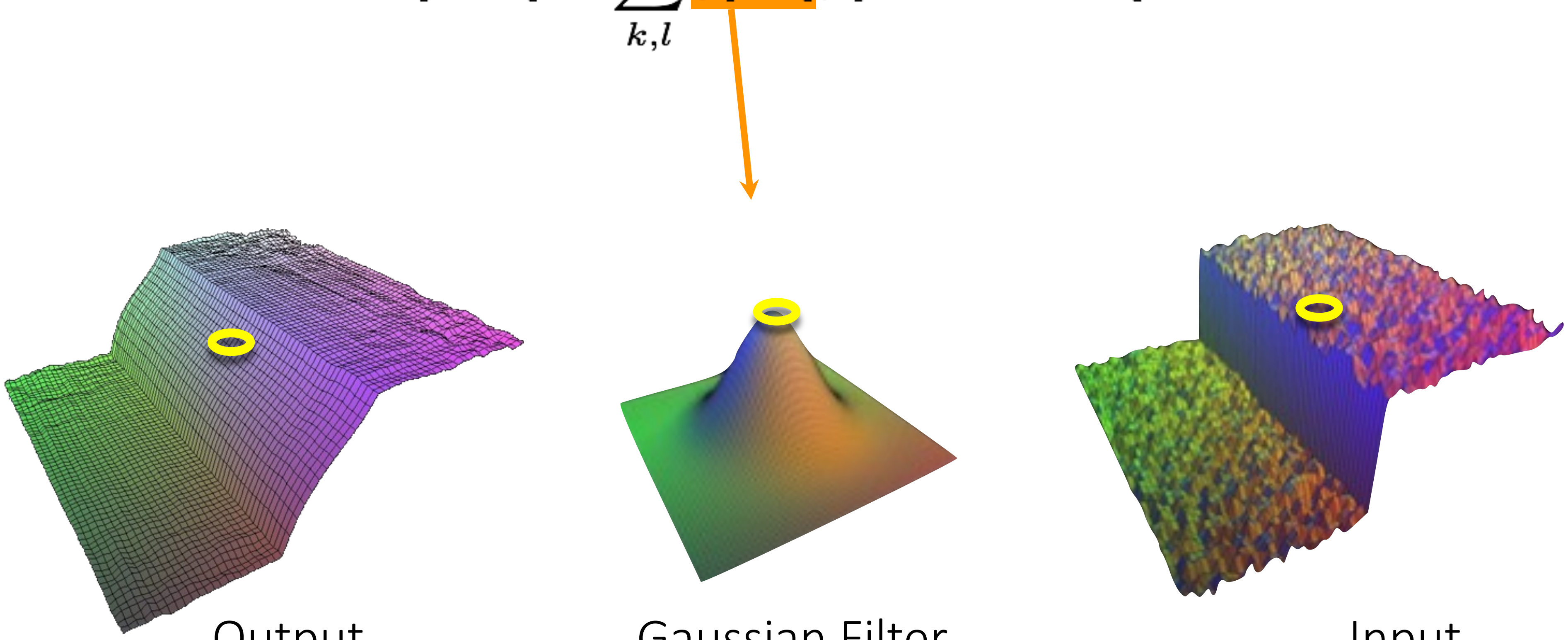
Smooths everything nearby (even edges)
Only depends on *spatial* distance

Bilateral filtering

Smooths 'close' pixels in space and intensity
Depends on *spatial* and *intensity* distance

Gaussian filtering visualization

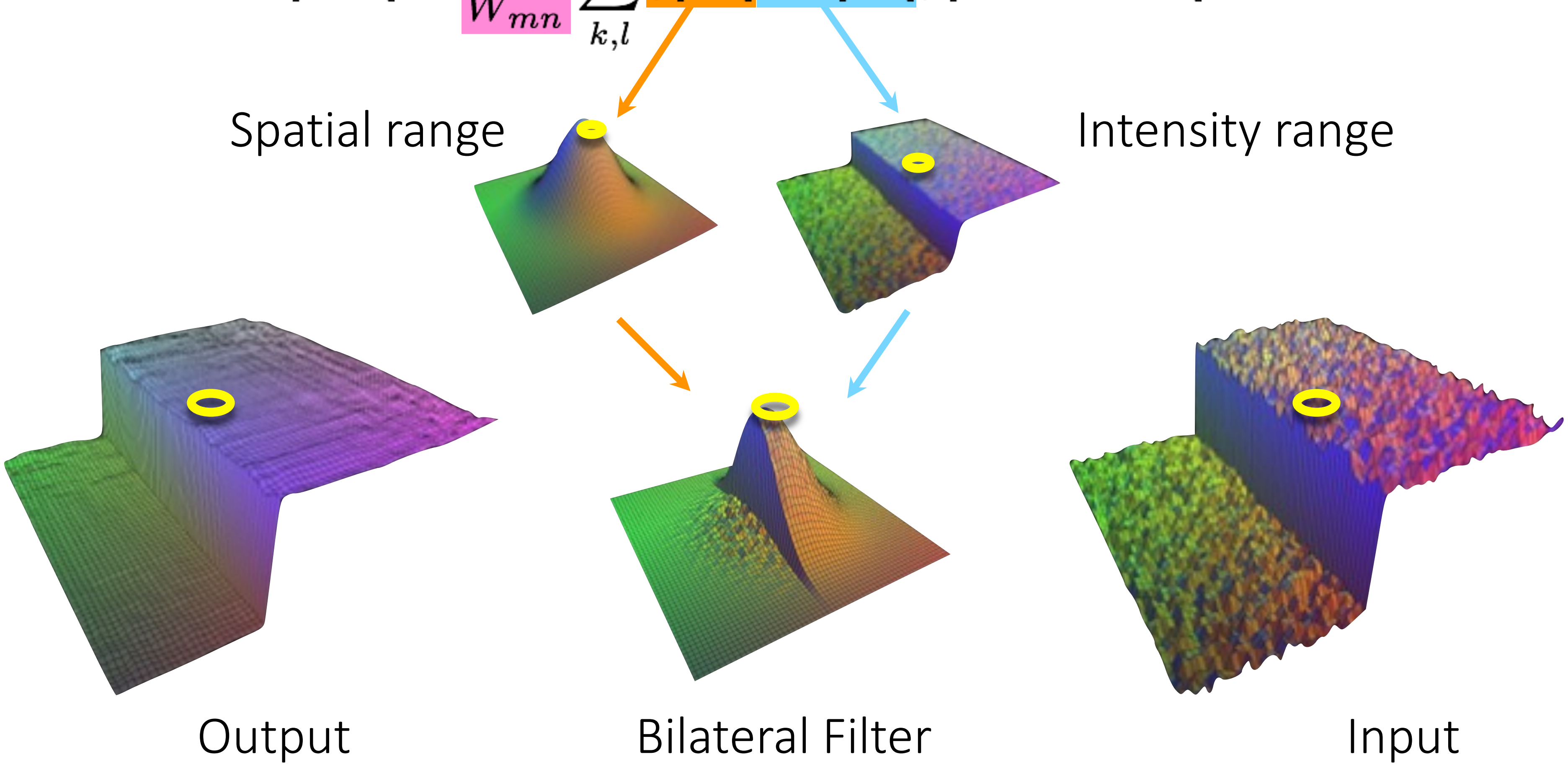
$$h[m,n] = \sum_{k,l} g[k,l] f[m+k, n+l]$$



Output Gaussian Filter Input

Bilateral filtering visualization

$$h[m,n] = \frac{1}{W_{mn}} \sum_{k,l} g[k,l] r_{mn}[k,l] f[m+k, n+l]$$



Exploring the bilateral filter parameter space

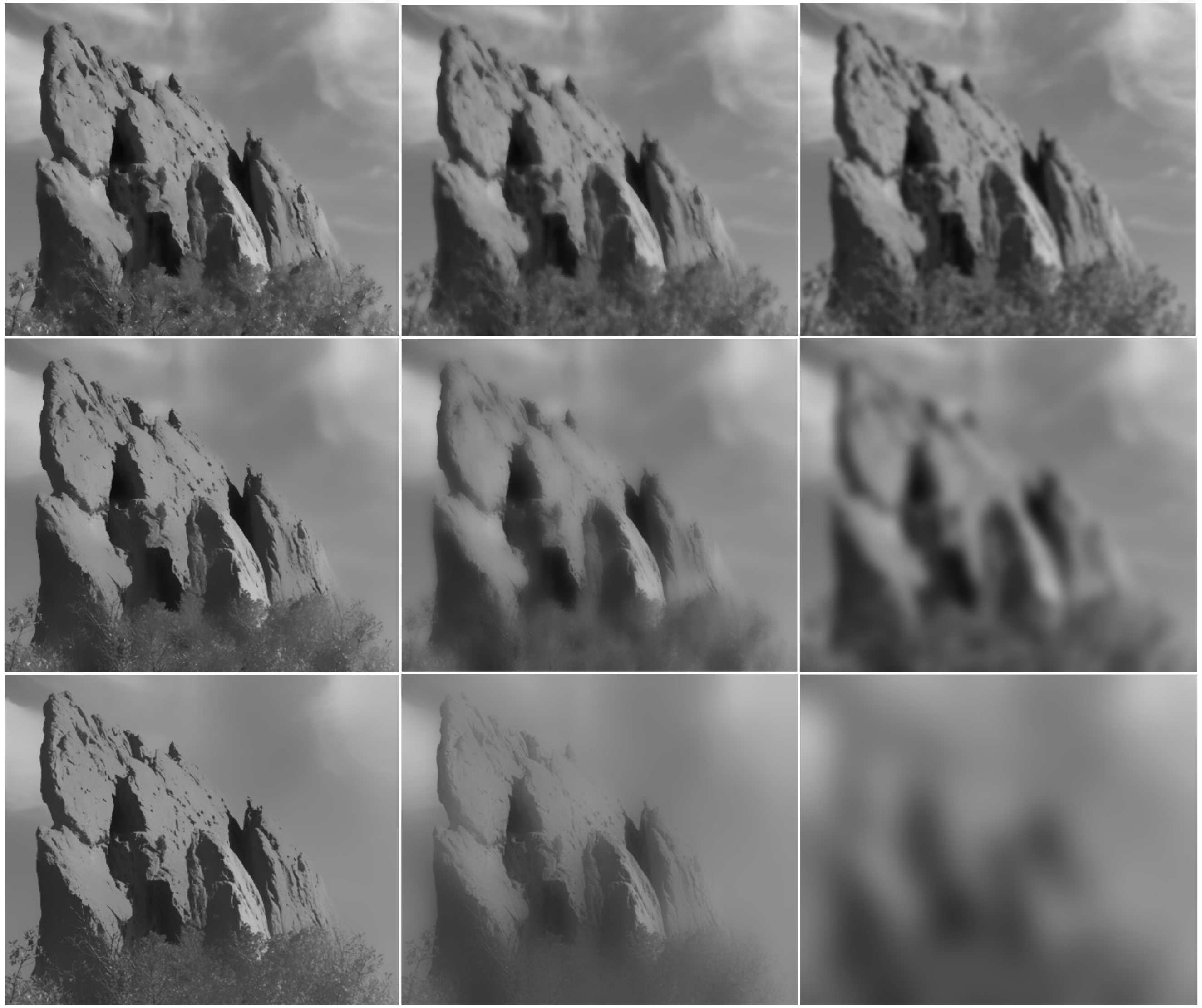
input

$\sigma_r = 0.1$ | $\sigma_r = 0.25$ | $\sigma_r = \infty$ (Gaussian blur)

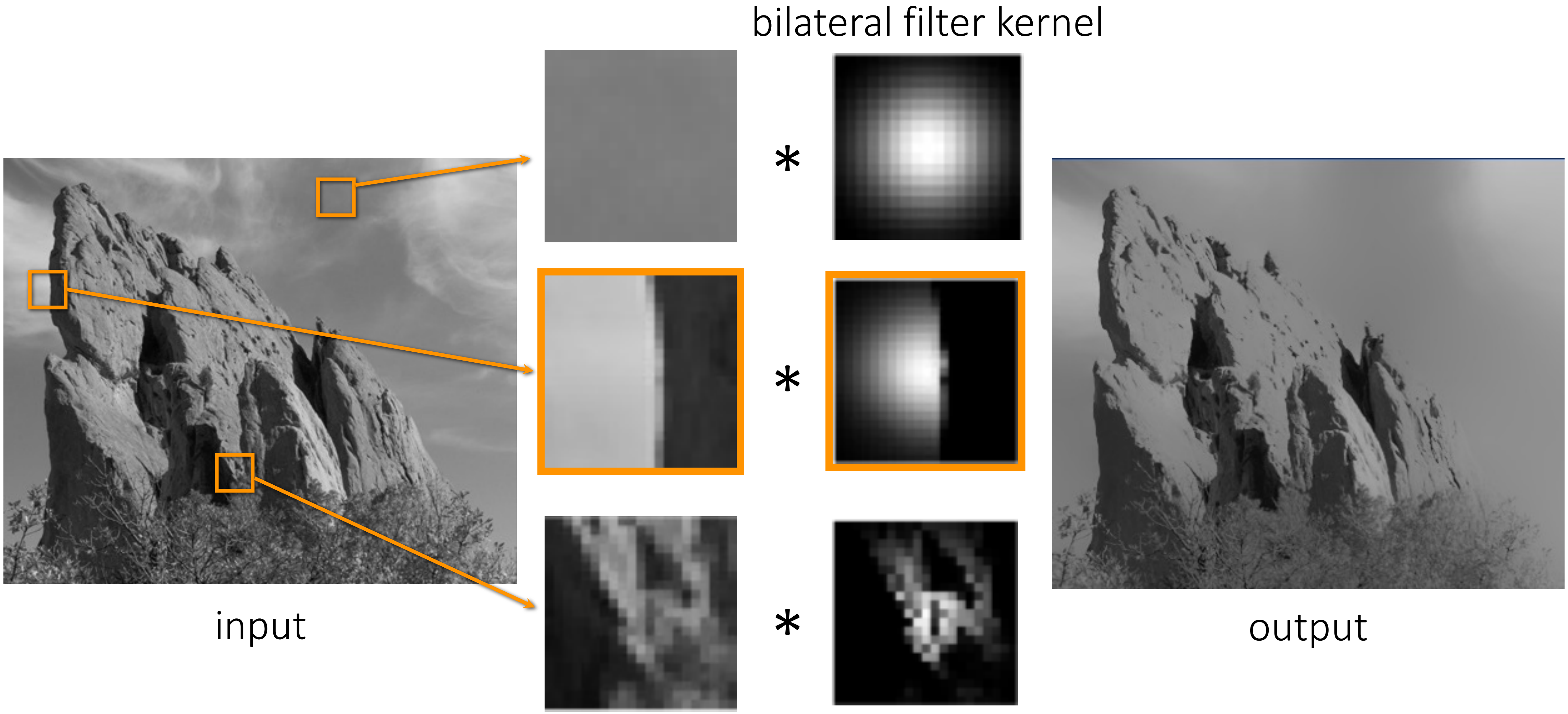
$\sigma_s = 2$

$\sigma_s = 6$

$\sigma_s = 18$

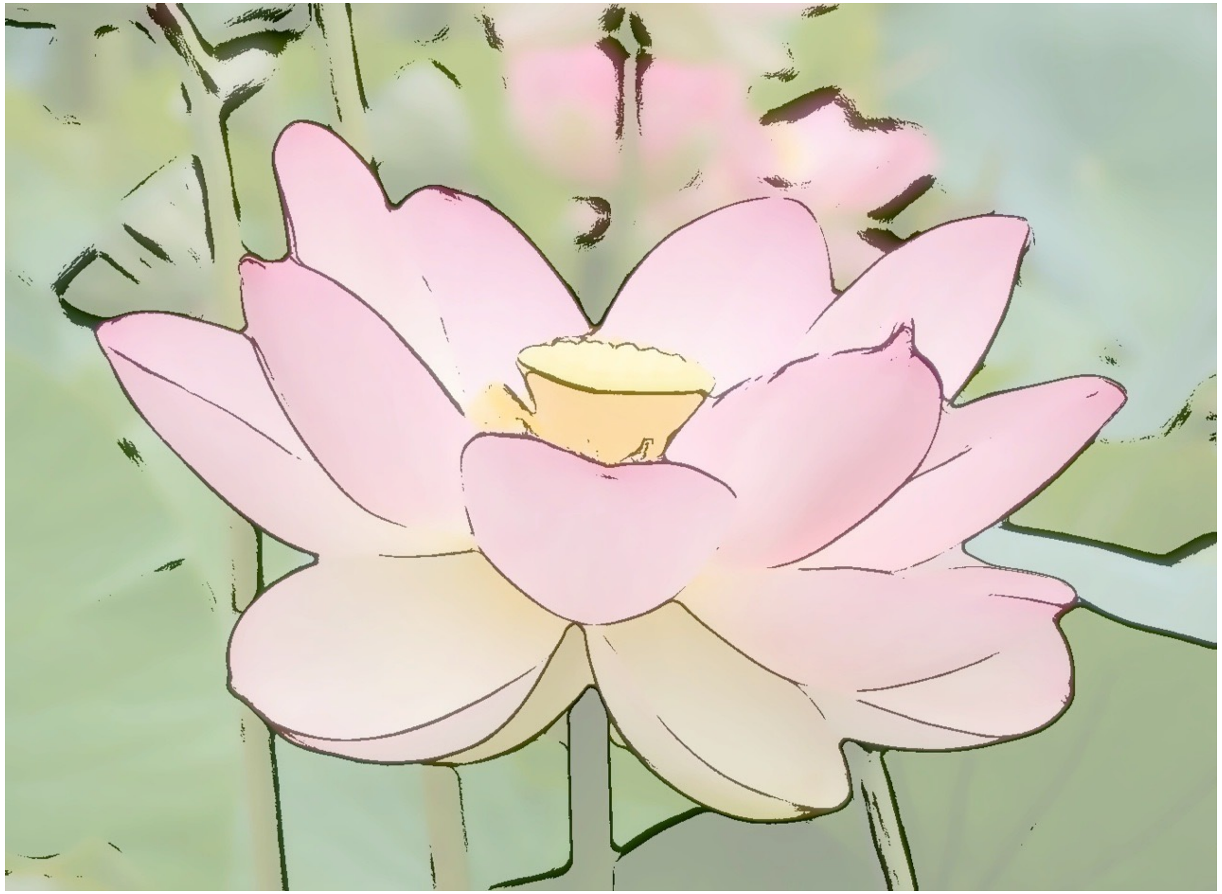


The bilateral filtering solution



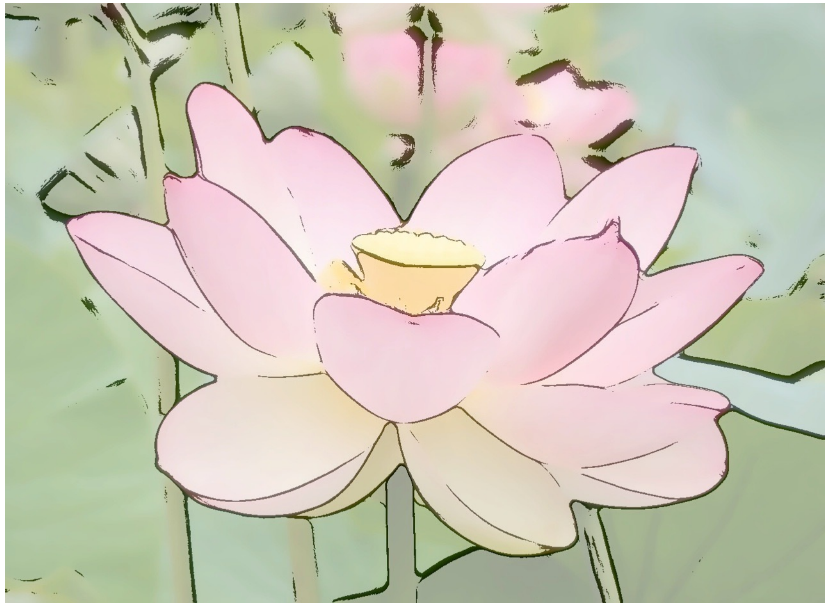
Do not blur if there is an edge!

Application: Cartoonization



How would you create this effect?

Application: Cartoonization



edges from bilaterally filtered image | bilaterally filtered image | cartoon rendition

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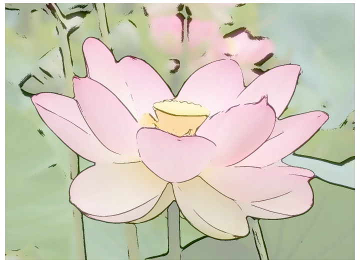
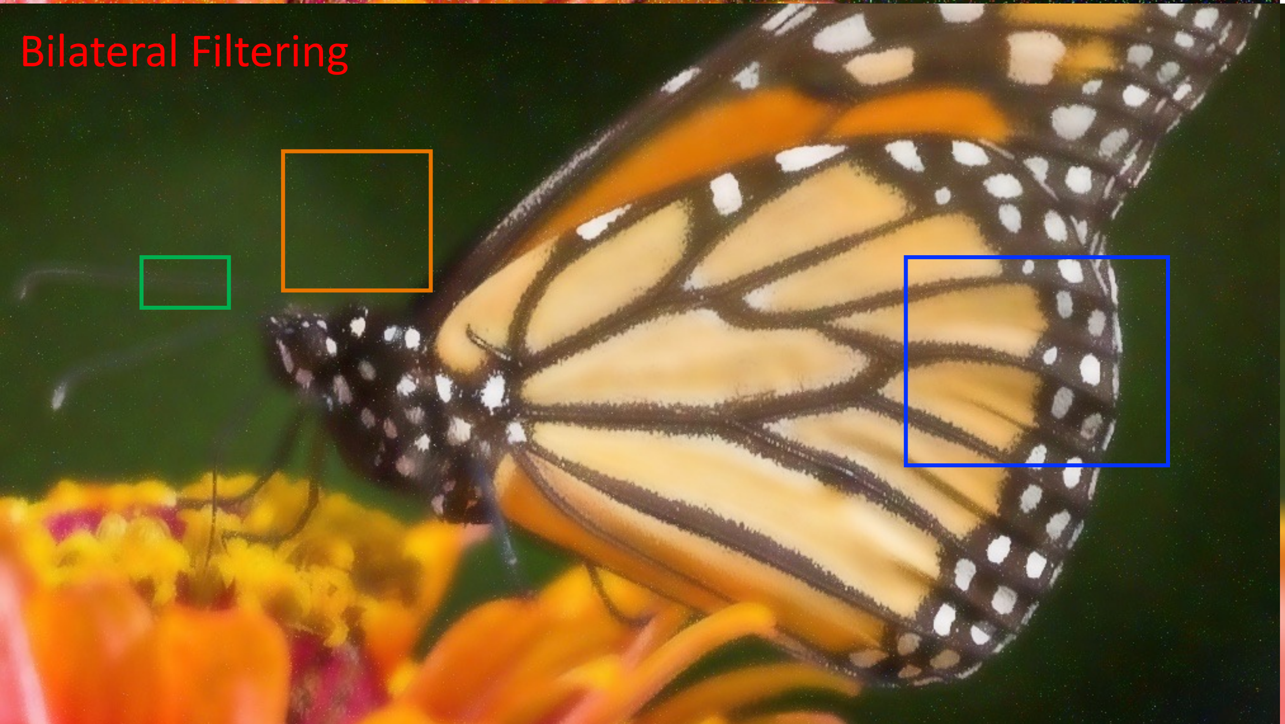


Application: Image Denoising with Bilateral Filtering

- Sharper edges
- Some thin edges may be reduced
- Flat regions are not fully smoothed



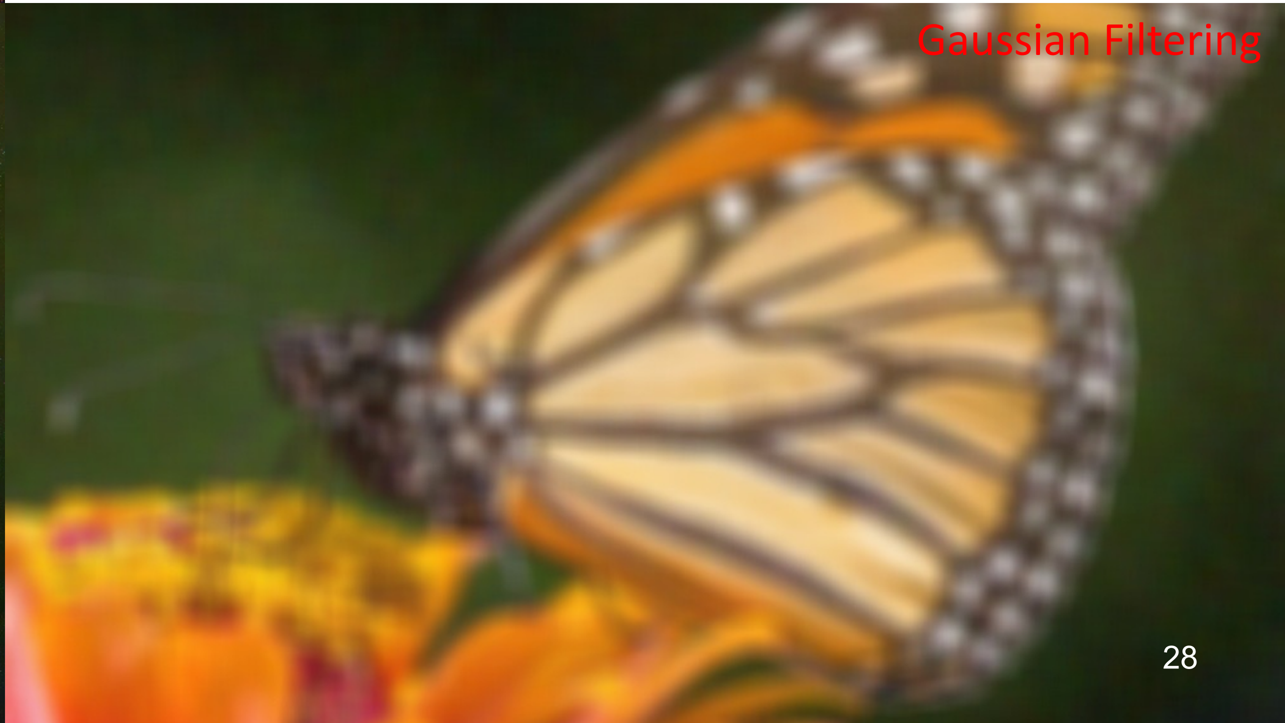
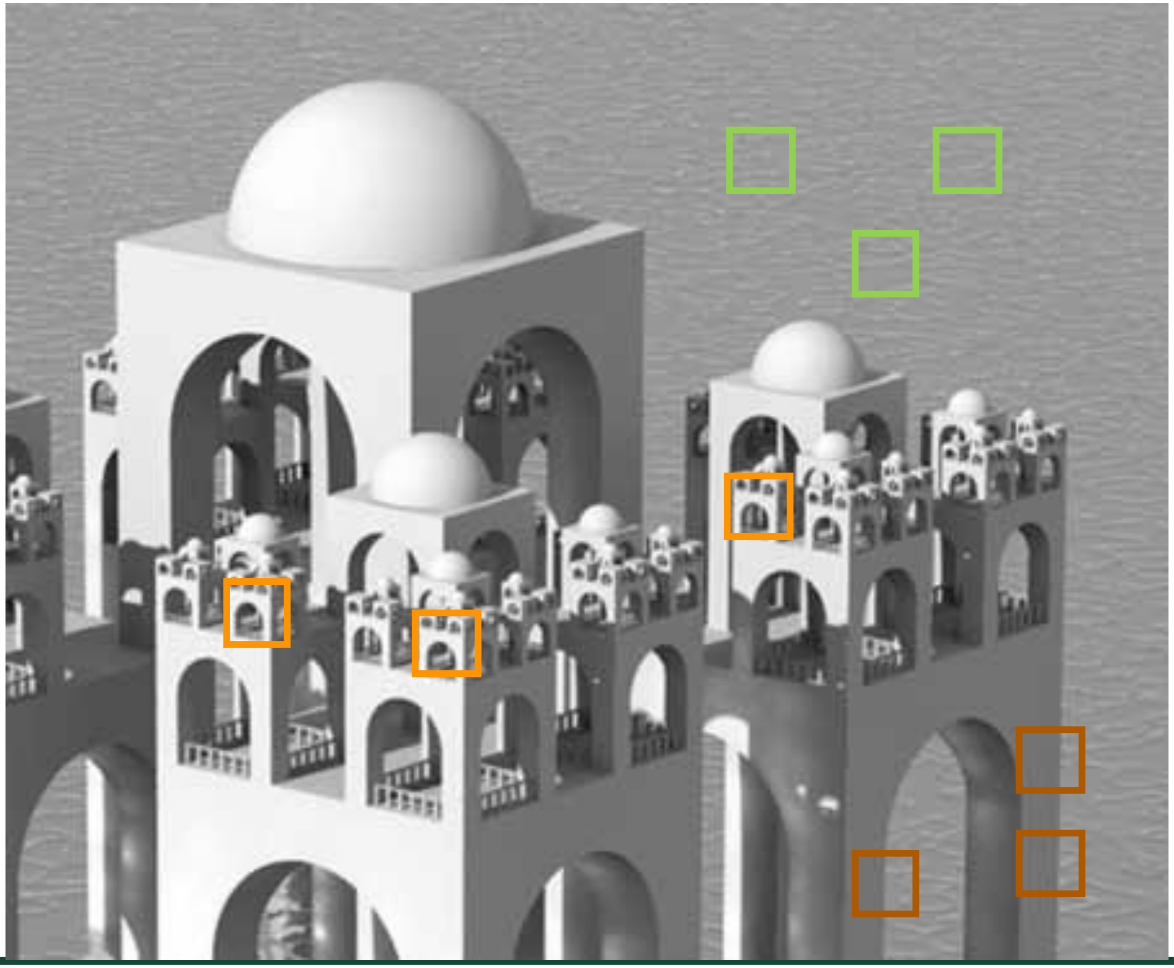


Image Prior: Non-local smoothness/redundancy



Small patches in natural images tend to redundantly appear multiple times

Non-local means Filter

No need to stop at neighborhood. Instead search *everywhere* in the image.

Given a pixel $f(p)$ at position $p = (p_x, p_y)$, the filter uses pixels in the whole image to update $f(p)$

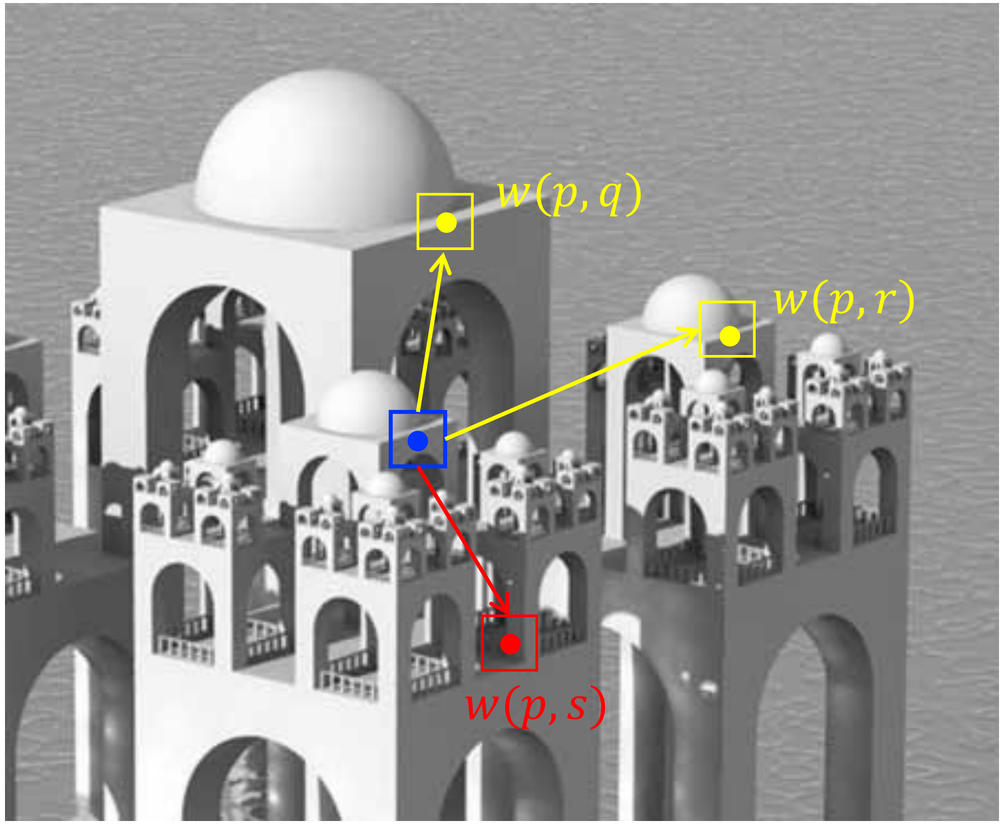
$$h(p) = \frac{1}{W}\sum_{q} w(p,q)f(q)$$

Weight: $w(p,q) = \exp(-\frac{SSD(p,q)}{2\sigma^2})$

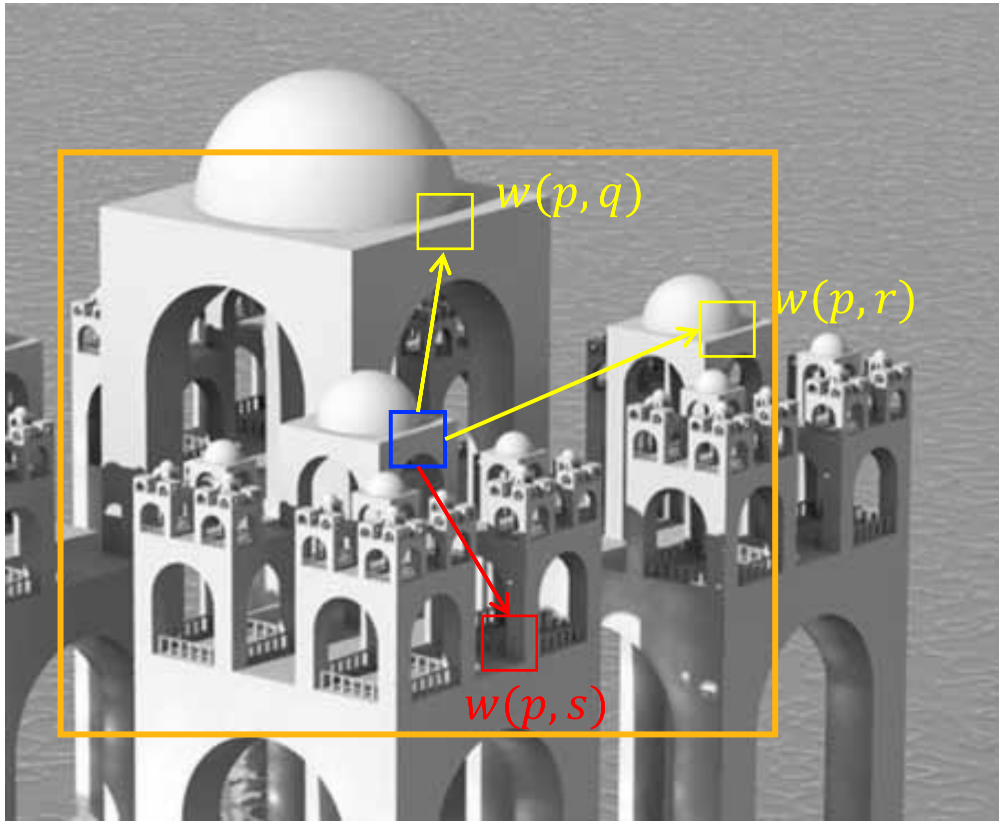
Sum of the squared difference between two patches

$$SSD(p,q) = \sum_{k=-n}^{n}\sum_{l=-n}^{n}\left(f\left(p_x+k, p_y+l\right) - f(q_x+k, q_y+l)\right)^2$$

$W = \sum_q w(p,q)$ is the normalization term



Fast Implementation of Non-local Means



Scan over the whole image to compute weights for each pixel is time-consuming

Implementation:

- set a search window (e.g., 21x21) with the target pixel position as the center
- only use pixels inside the window to compute weights based on patch similarity

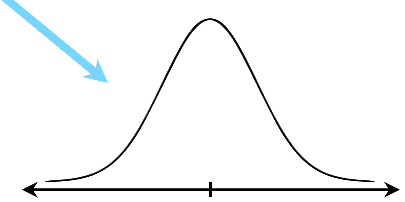
Patch size (e.g., 5x5, 7x7) is much smaller than the window size

Non-local means vs bilateral filtering

Non-local means filtering

$$h[m,n] = \frac{1}{W_{mn}} \sum_{k,l} r_{mn}[k,l] f[m+k, n+l]$$

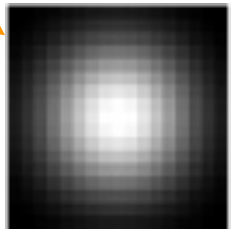
Bilateral filtering



$x = f[m,n] - f[m+k,n+l]$

Intensity range weighting: favor *similar* pixels (patches in case of non-local means)

$$h[m,n] = \frac{1}{W_{mn}} \sum_{k,l} g[k,l] r_{mn}[k,l] f[m+k, n+l]$$



Spatial weighting: favor *nearby* pixels


Nonlocal Means Filtering
Noisy Image
Bilateral Filtering
Gaussian Filtering

Summary

Gaussian filtering

Smooths everything nearby (even edges)
Only depends on *spatial* distance

Bilateral filtering

Smooths ‘close’ pixels in space and intensity
Depends on *spatial* and *intensity* distance

Non-local means

Smooths similar patches no matter how far away
Only depends on *intensity* distance

Further Reading

Chapters 3.3.1 and 3.3.2, Computer Vision: Algorithms and Applications, Richard Szeliski

https://en.wikipedia.org/wiki/Non-local_means