

BBM444

FUNDAMENTALS OF COMPUTATIONAL PHOTOGRAPHY

Lecture #05 – Edge-Aware Filtering

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HACETTEPE
UNIVERSITY
COMPUTER
VISION LAB

Today's Lecture

- Gaussian filtering
- Sharpening
- Bilateral filter
- Non-local means filter
- RegCov smoothing
- Rolling guidance filter

Disclaimer: The material and slides for this lecture were borrowed from

- Ioannis Gkioulekas' 15-463/15-663/15-862 "Computational Photography" class
- Wojciech Jarosz's CS 89.15/189.5 "Computational Aspects of Digital Photography" class
- Steve Marschner's CS6640 "Computational Photography" class
- Kaiming He's slides on Guided Image Filtering

Filtering

- The name “filter” is borrowed from frequency domain processing
- Accept or reject certain frequency components
- Fourier (1807):
Periodic functions could be represented as a weighted sum of sines and cosines

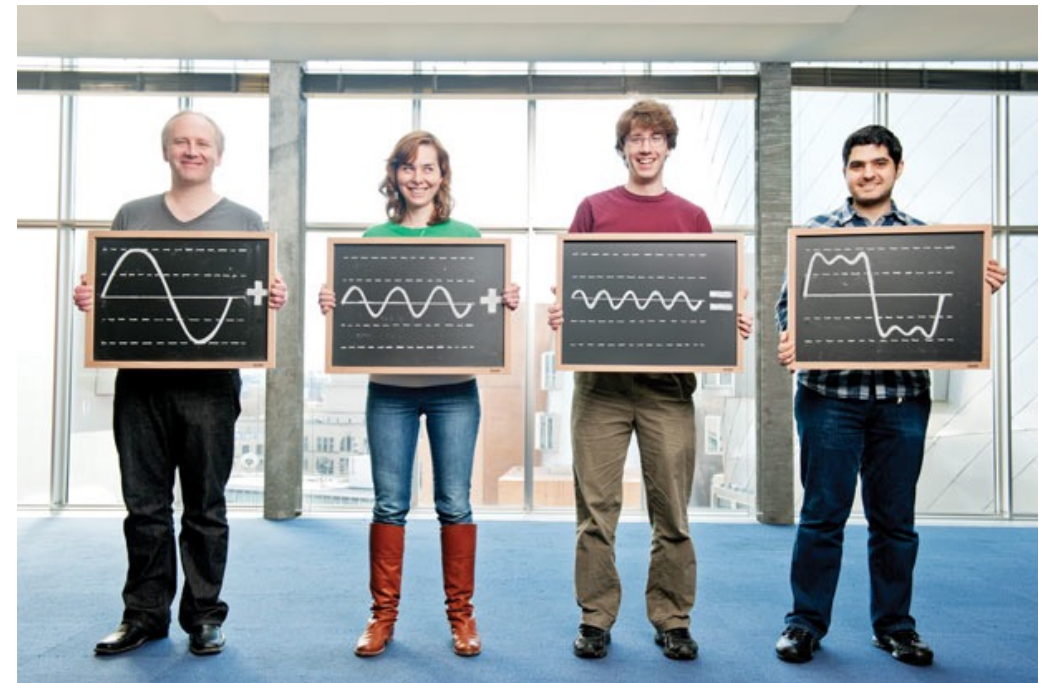
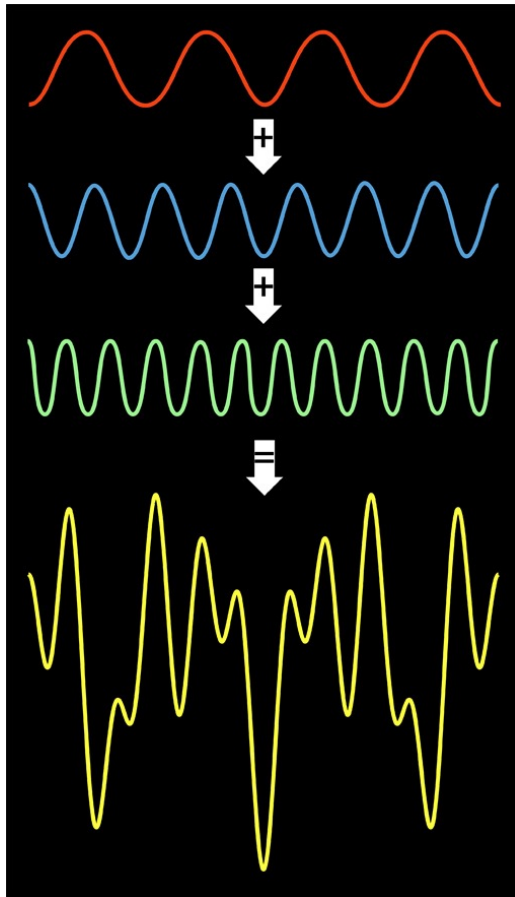


Image courtesy of Technology Review

Signals

- A signal is composed of low and high frequency components



low frequency components: smooth / piecewise smooth

Neighboring pixels have similar brightness values

You're within a region

high frequency components: oscillatory

Neighboring pixels have different brightness values

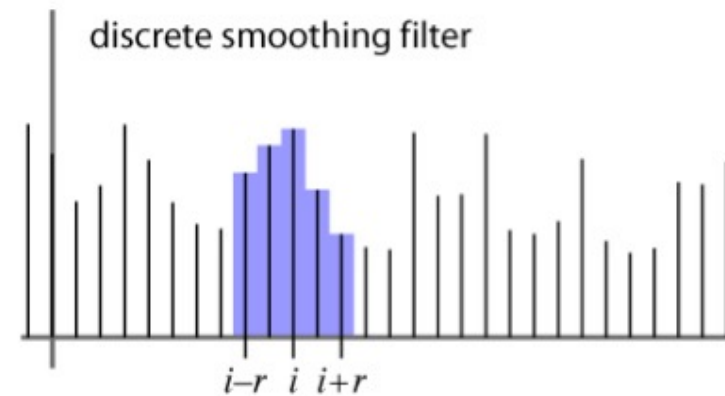
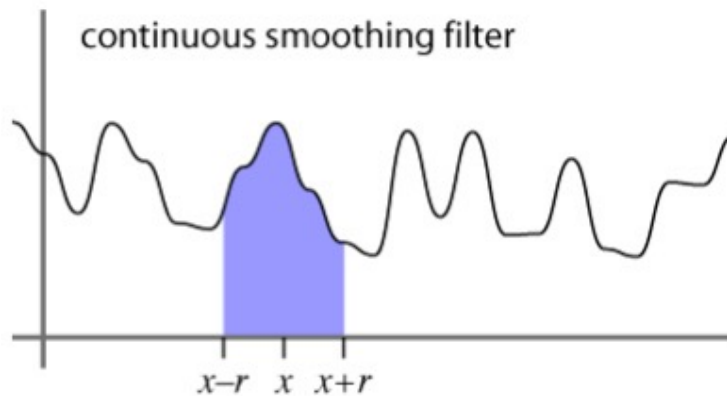
You're either at the edges or noise points

Image Filtering

- Idea: Use the information coming from the neighboring pixels for processing
- Design a transformation function of the local neighborhood at each pixel in the image
 - Function specified by a “filter” or mask saying how to combine values from neighbors.
- Various uses of filtering:
 - Enhance an image (denoise, resize, etc)
 - Extract information (texture, edges, etc)
 - Detect patterns (template matching)

Filtering

- Processing done on a function
 - can be executed in continuous form (e.g. analog circuit)
 - but can also be executed using sampled representation
- Simple example: smoothing by averaging
- Can be modeled mathematically by convolution



Discrete convolution

- Simple averaging:

$$b_{\text{smooth}}[i] = \frac{1}{2r + 1} \sum_{j=i-r}^{i+r} b[j]$$

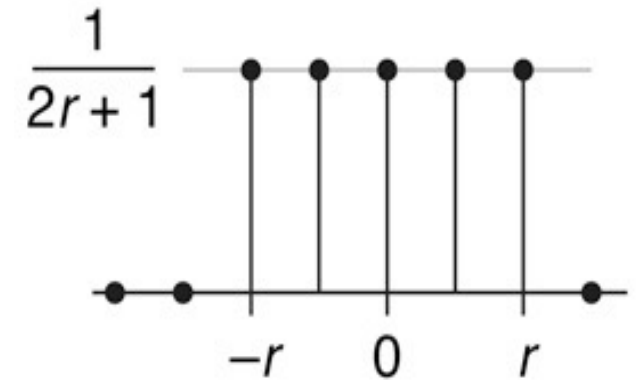
- every sample gets the same weight
- Convolution: same idea but with weighted average

$$(a \star b)[i] = \sum_j a[j]b[i - j]$$

- each sample gets its own weight (normally zero far away)
- This is all convolution is: it is a moving weighted average

Filters

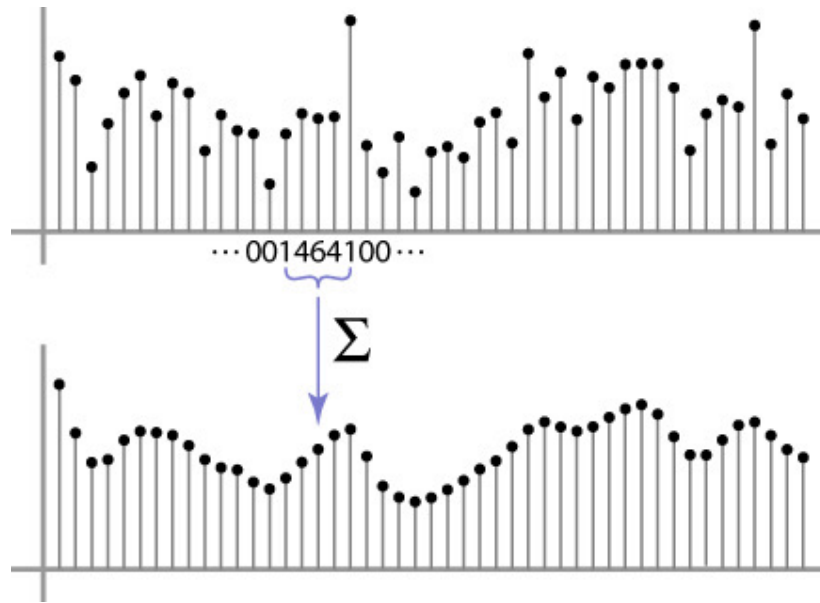
- Sequence of weights $a[j]$ is called a filter
- Filter is nonzero over its region of support
 - usually centered on zero: support radius r
- Filter is normalized so that it sums to 1.0
 - this makes for a weighted average, not just any old weighted sum
- Most filters are symmetric about 0
 - since for images we usually want to treat left and right the same



a box filter

Convolution and filtering

- Convolution applies with any sequence of weights
- Example: bell curve (gaussian-like) [..., 1, 4, 6, 4, 1, ...]/16



Discrete filtering in 2D

- Same equation, one more index

$$(a \star b)[i, j] = \sum_{i', j'} a[i', j'] b[i - i', j - j']$$

- now the filter is a rectangle you slide around over a grid of numbers
- Usefulness of associativity
- often apply several filters one after another: $((a * b_1) * b_2) * b_3$
- this is equivalent to applying one filter: $a * (b_1 * b_2 * b_3)$

Moving Average In 2D

$F[x, y]$

| | | | | | | | | | | |
|---|---|----|----|----|----|----|----|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 | 0 |
| 0 | 0 | 0 | 90 | 0 | 90 | 90 | 90 | 0 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 90 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

$G[x, y]$

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Moving Average In 2D

$F[x, y]$

| | | | | | | | | | |
|---|---|----|----|----|----|----|----|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 0 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 90 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

$G[x, y]$

| | | | | | | | | | |
|--|---|----|--|--|--|--|--|--|--|
| | | | | | | | | | |
| | 0 | 10 | | | | | | | |
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Moving Average In 2D

$$F[x, y]$$

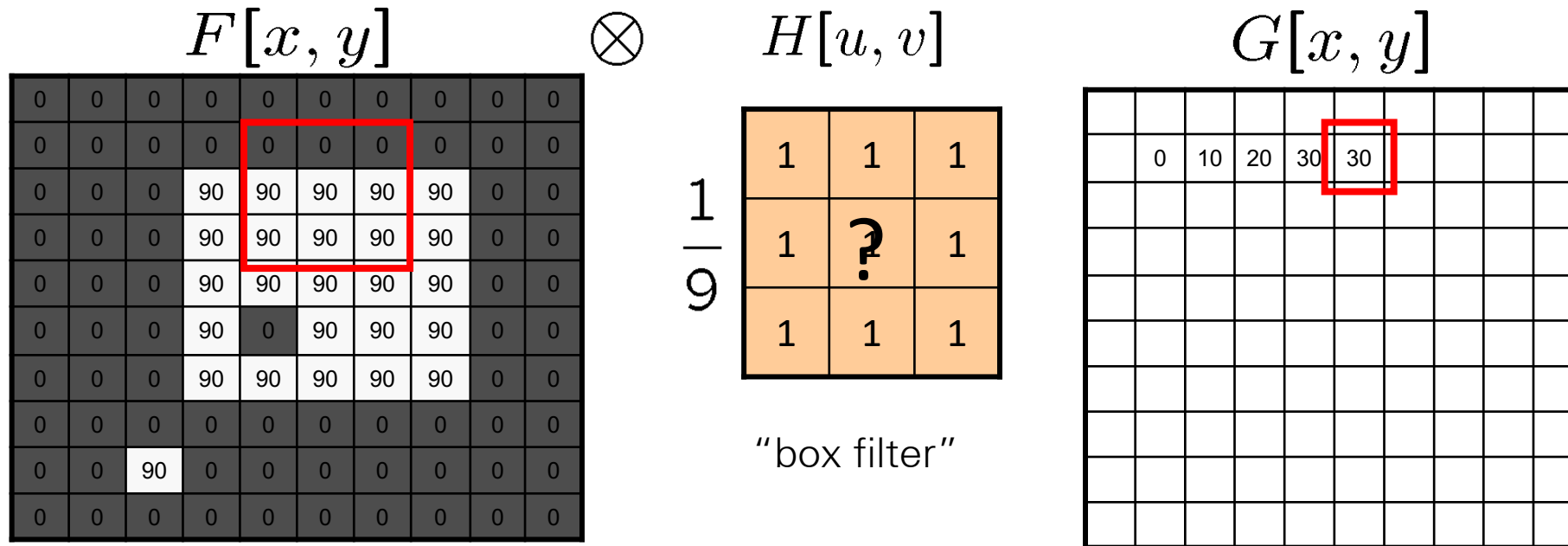
| | | | | | | | | | |
|---|---|----|----|----|----|----|----|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 0 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 90 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

$$G[x, y]$$

| | | | | | | | | | |
|--|----|----|----|----|----|----|----|----|--|
| | | | | | | | | | |
| | 0 | 10 | 20 | 30 | 30 | 30 | 20 | 10 | |
| | 0 | 20 | 40 | 60 | 60 | 60 | 40 | 20 | |
| | 0 | 30 | 60 | 90 | 90 | 90 | 60 | 30 | |
| | 0 | 30 | 50 | 80 | 80 | 90 | 60 | 30 | |
| | 0 | 30 | 50 | 80 | 80 | 90 | 60 | 30 | |
| | 0 | 20 | 30 | 50 | 50 | 60 | 40 | 20 | |
| | 10 | 20 | 30 | 30 | 30 | 30 | 20 | 10 | |
| | 10 | 10 | 10 | 0 | 0 | 0 | 0 | 0 | |
| | | | | | | | | | |

Averaging Filter

- What values belong in the kernel H for the moving average example?



$$G = H \otimes F$$

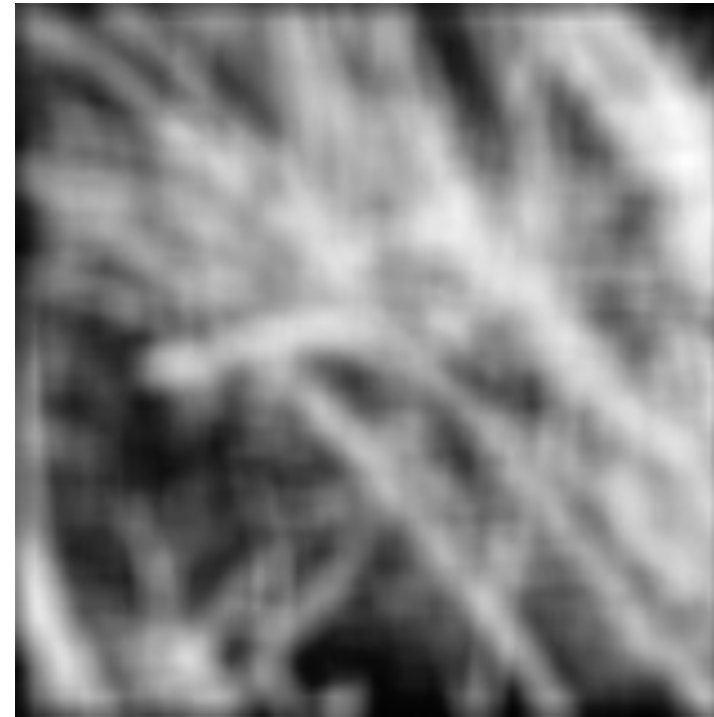
Smoothing by averaging



depicts box filter:
white = high value, black = low value



original



filtered

Gaussian Filtering

Gaussian Filter

- What if we want nearest neighboring pixels to have the most influence on the output?

| | | | | | | | | | |
|---|---|----|----|----|----|----|----|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 0 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 90 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

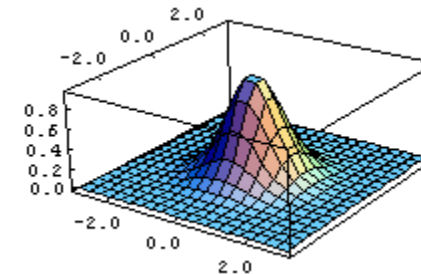
$F[x, y]$

| | | |
|---|---|---|
| 1 | 2 | 1 |
| 2 | 4 | 2 |
| 1 | 2 | 1 |

$H[u, v]$

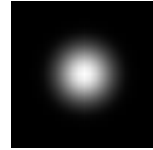
This kernel is an approximation of a 2d Gaussian function:

$$h(u, v) = \frac{1}{2\pi\sigma^2} e^{-\frac{u^2+v^2}{\sigma^2}}$$



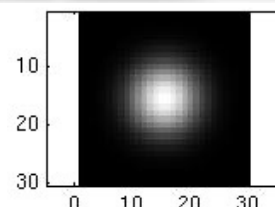
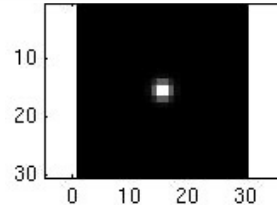
- Removes high-frequency components from the image ("low-pass filter").

Smoothing with a Gaussian

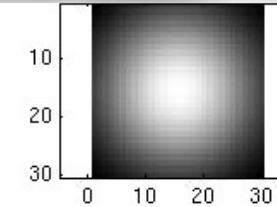


Smoothing with a Gaussian

Parameter σ is the “scale” / “width” / “spread” of the Gaussian kernel, and controls the amount of smoothing.



...



Strategy for Smoothing Images

- Images are not smooth because adjacent pixels are different.
- Smoothing = making adjacent pixels look more similar.
- Smoothing strategy
 pixel \sim average of its neighbors

Sharpening

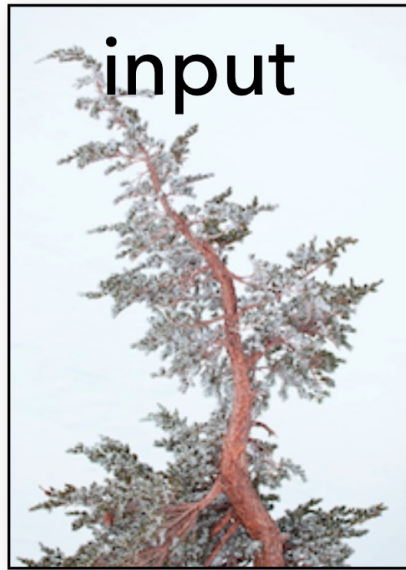
How can we sharpen?

- Blurring was easy
- Sharpening is not as obvious

How can we sharpen?

- Blurring was easy
- Sharpening is not as obvious
- Idea: amplify the stuff not in the blurry image
- $\text{output} = \text{input} + k * (\text{input} - \text{blur}(\text{input}))$

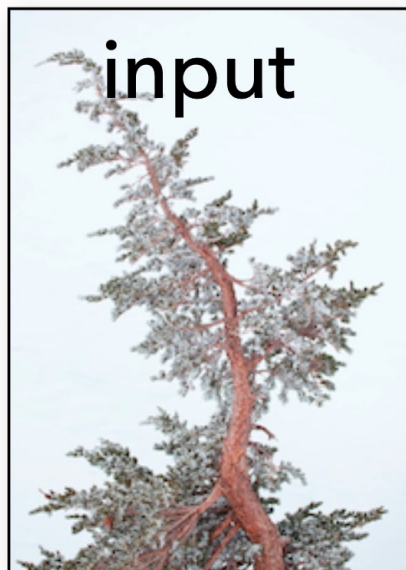
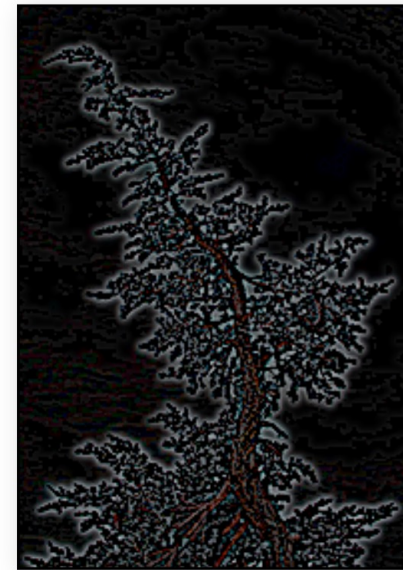
Sharpening



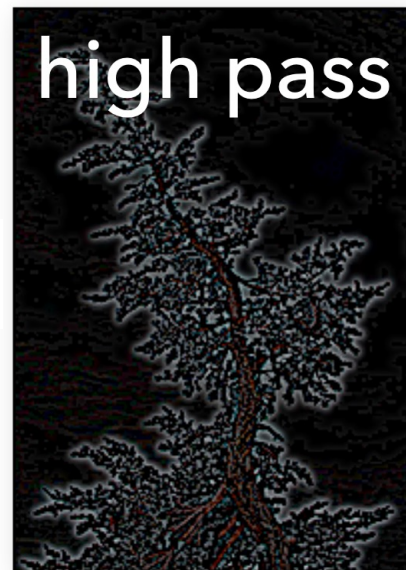
-



=



+k*



=



Sharpening: kernel view

- Recall

$$f' = f + k * (f - f \otimes g)$$

f is the input

f' is a sharpened image

g is a blurring kernel

k is a scalar controlling the strength of sharpening

Sharpening: kernel view

- Recall

$$f' = f + k * (f - f \otimes g)$$

- Denote δ the Dirac kernel (pure impulse)

$$f = f \otimes \delta$$

Sharpening: kernel view

- Recall

$$f' = f + k * (f - f \otimes g)$$

$$f' = f \otimes \delta + k * (f \otimes \delta - f \otimes g)$$

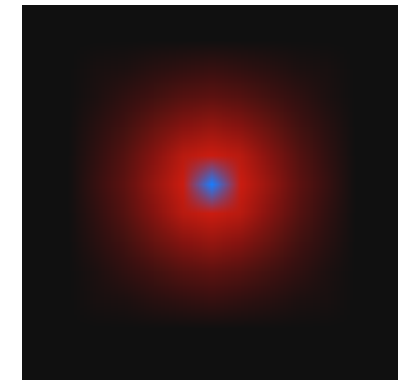
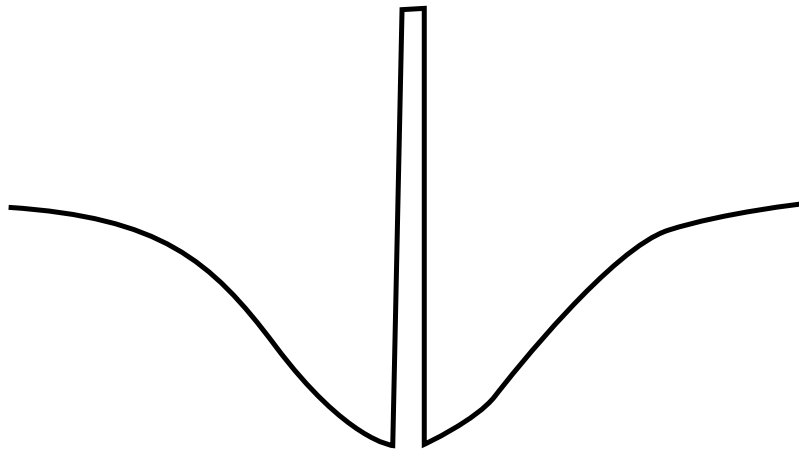
$$f' = f \otimes ((k + 1)\delta - g)$$

- Sharpening is also a convolution

Sharpening kernel

- Note: many other sharpening kernels exist (just like we saw multiple blurring kernels)
- Amplify the difference between a pixel and its neighbors

$$f' = f \otimes ((k + 1)\delta - g)$$



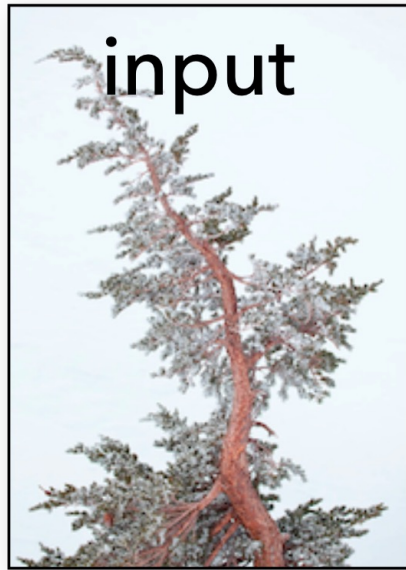
blue: positive
red: negative

Alternate interpretation

- $\text{out} = \text{input} + k * (\text{input} - \text{blur}(\text{input}))$
- $\text{out} = (1 + k) * \text{input} - k * \text{blur}(\text{input})$
- $\text{out} = \text{lerp}(\text{blur}(\text{input}), \text{input}, 1+k)$

linearly extrapolate from the blurred image “past” the original input image

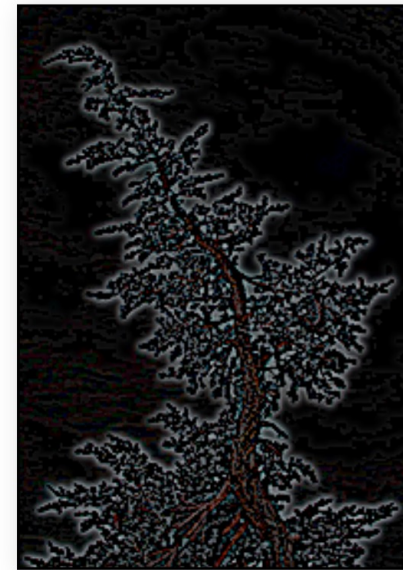
Sharpening



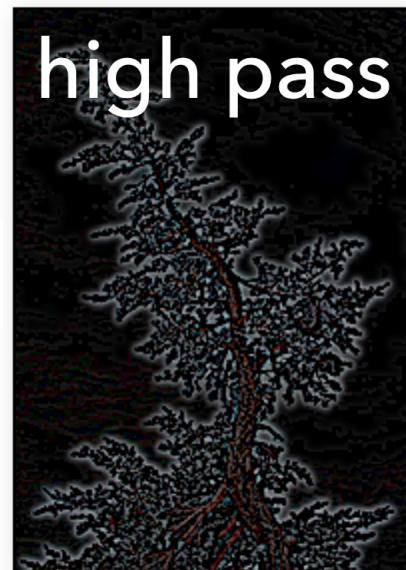
-



=



+k*

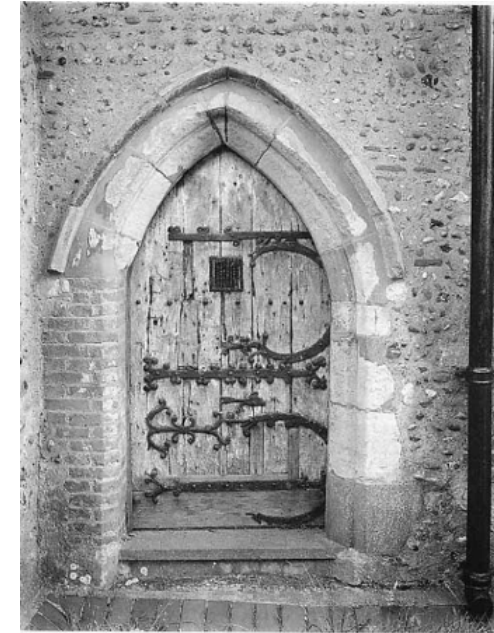
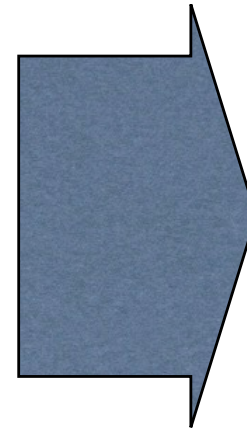
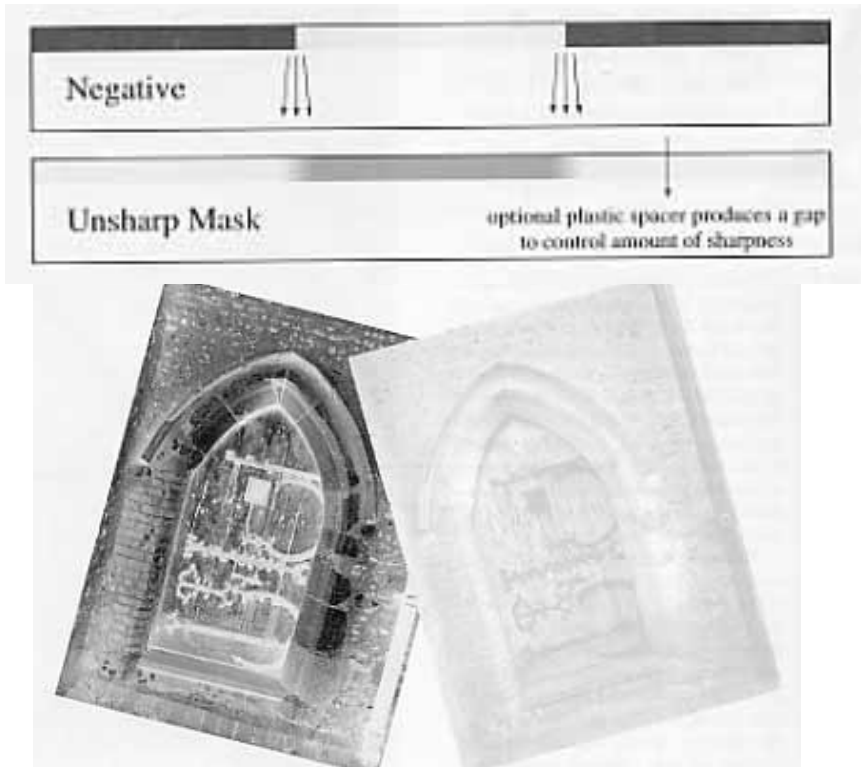


=



Unsharp mask

- Sharpening is often called “unsharp mask” because photographers used to sandwich a negative with a blurry positive film in order to sharpen

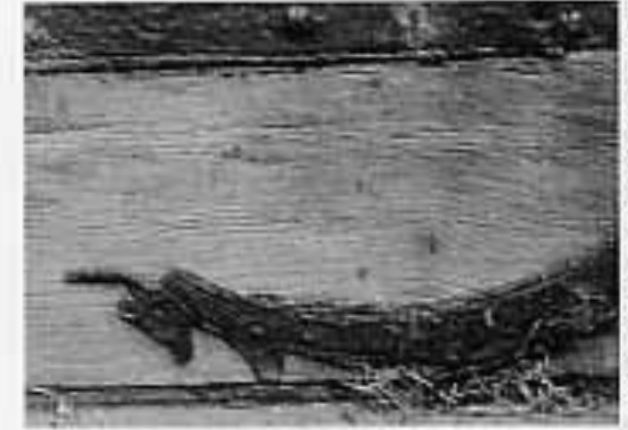


Unsharp mask

Fig.4: The two examples here show a detail of the brickwork to the left of the church door. The one on the left was printed with the negative alone – the one on the right was printed with both negative and mask as a sandwich. The increase in local contrast and edge sharpness is minute, but clearly visible. Grade 2.5 was used for the straight print but increased to 4.5 for the sandwiched image to compensate for the reduced contrast.



Fig.5: These two examples show a detail of the lower right hand side of the church door. Here the difference in sharpness is clearly visible between the (left) negative and (right) sandwich prints.



Problem with excess

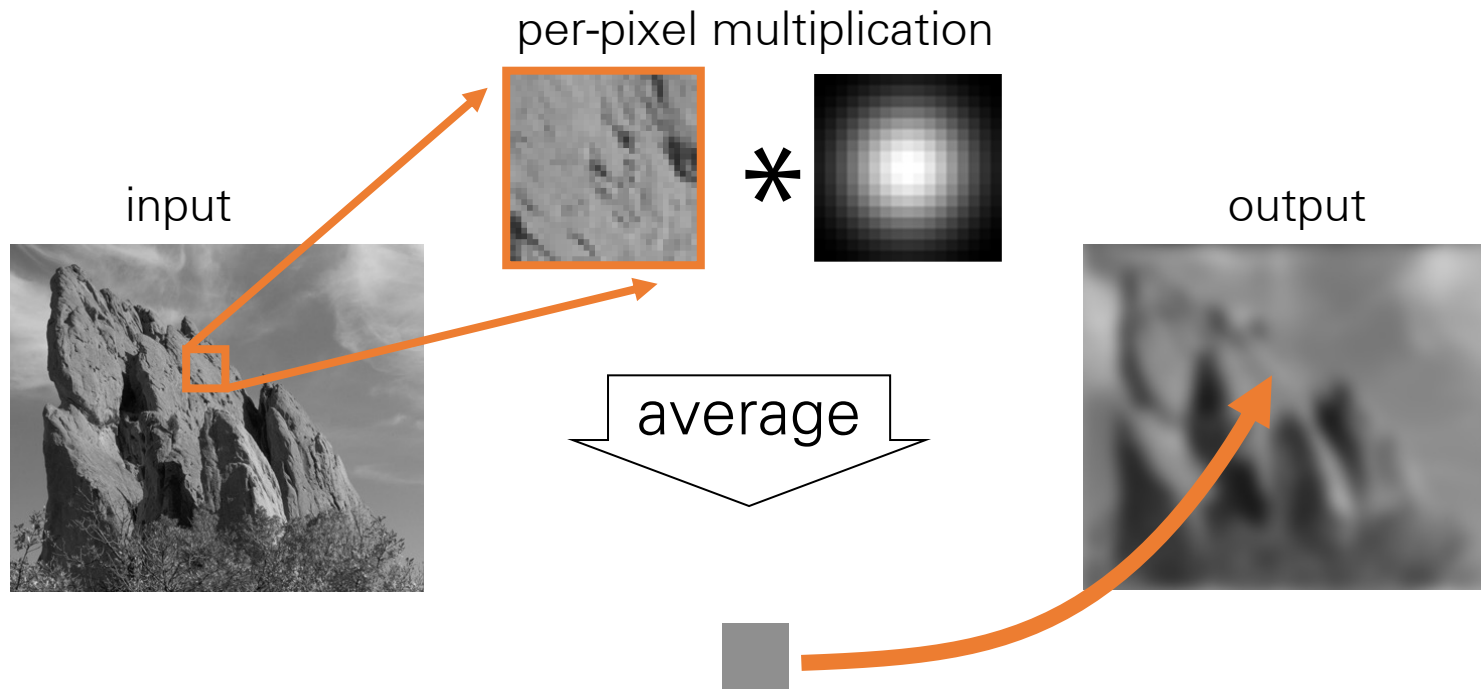
- Haloes around strong edges



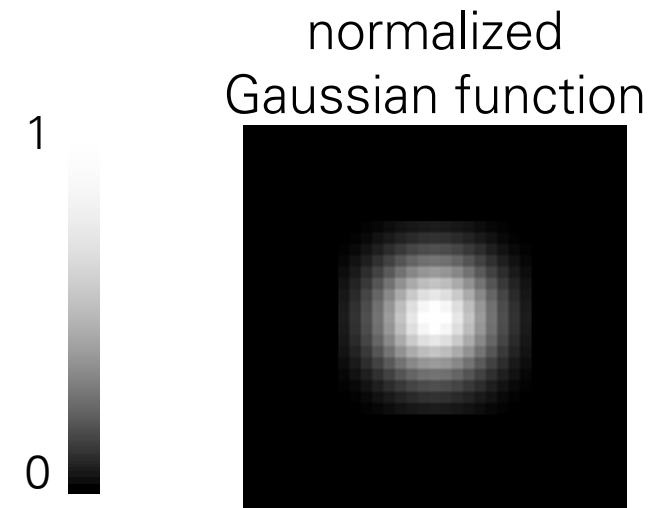
Bilateral Filter

Gaussian Filter

Idea: weighted average of pixels.



$$GB[I]_p = \sum_{q \in S} G_\sigma(\|p - q\|) I_q$$



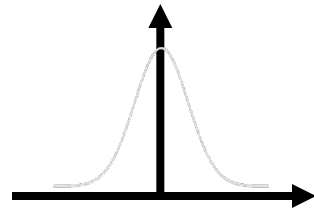
Spatial Parameter



input

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

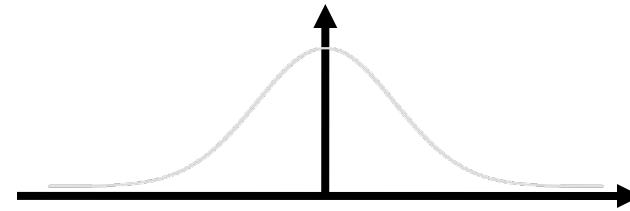
size of the window



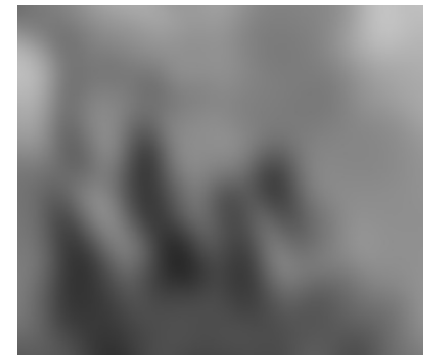
small σ



limited smoothing



large σ



strong smoothing

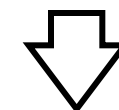
Properties of Gaussian Blur

- Weights independent of spatial location
 - linear convolution
 - well-known operation
 - efficient computation (recursive algorithm, FFT...)
- Does smooth images
- But smooths too much:
edges are blurred.
 - Only spatial distance matters
 - No edge term

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

space

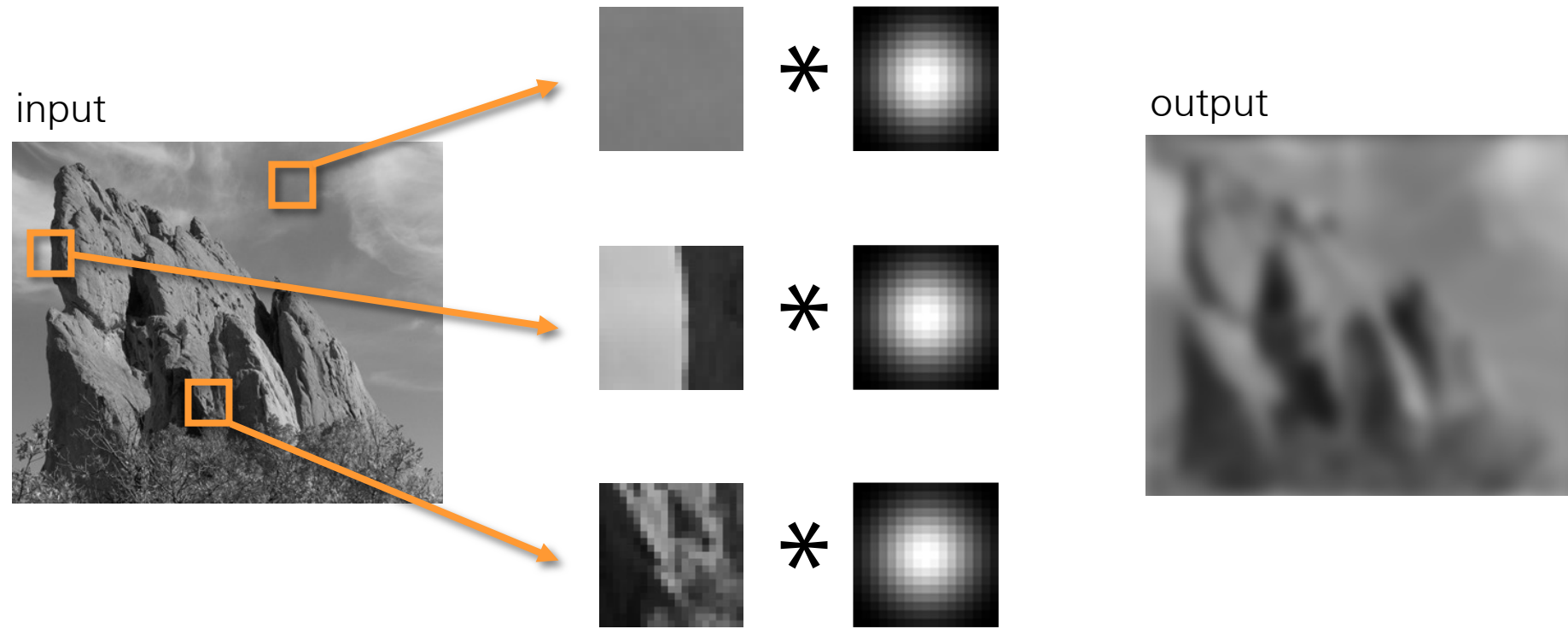
input



output

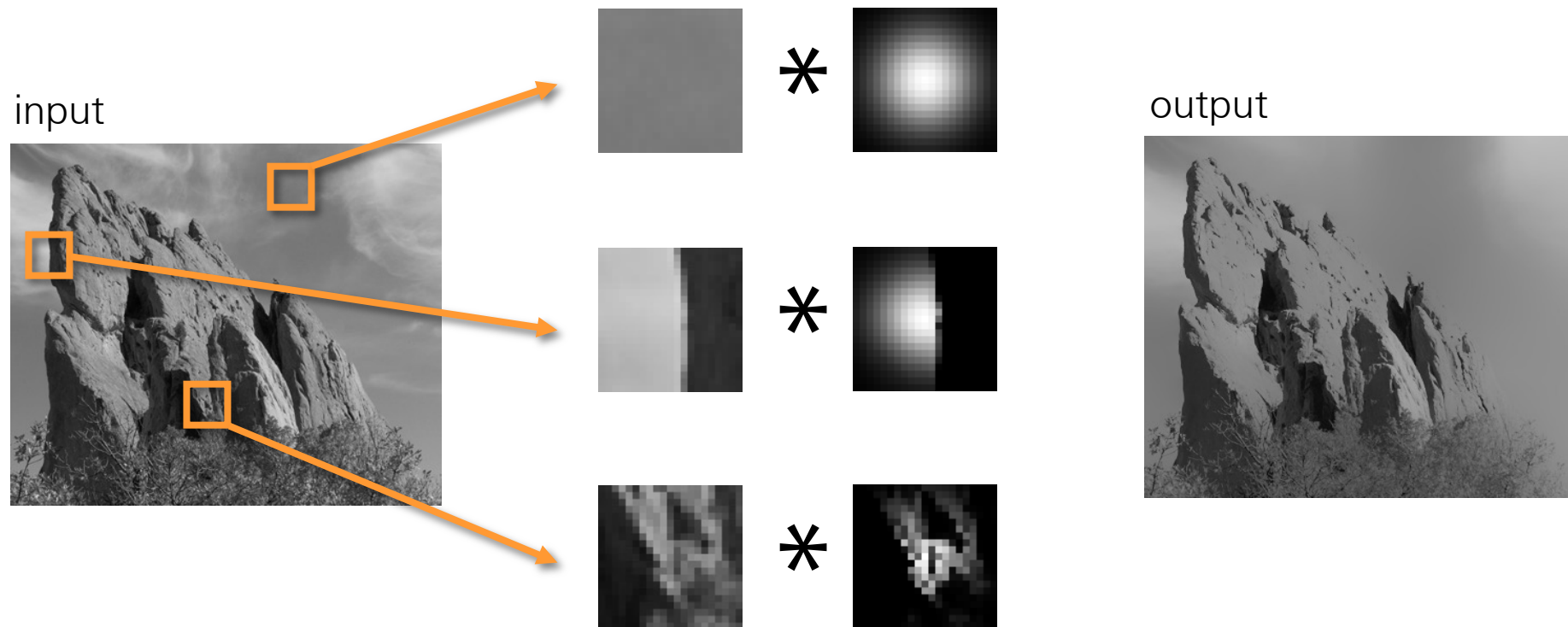


Blur Comes from Averaging across Edges



Same Gaussian kernel everywhere.

Bilateral Filter: No Averaging across Edges



The kernel shape depends on the image content.

Bilateral Filter: An Additional Edge Term

Same idea: weighted average of pixels.

$$BF[I]_p = \frac{1}{W_p} \sum_{q \in \mathcal{S}} G_{\sigma_s}(\|\mathbf{p} - \mathbf{q}\|) G_{\sigma_r}(|I_p - I_q|) I_q$$

new

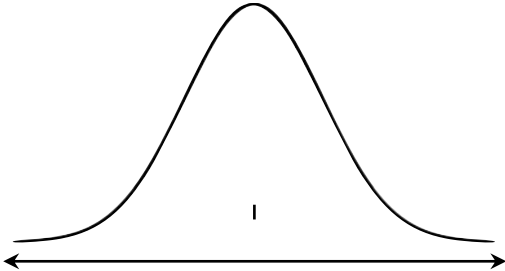
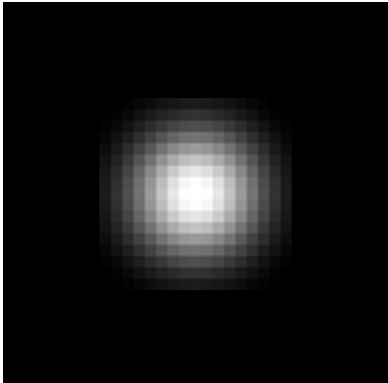
not new

new

normalization factor

space weight

range weight



Bilateral Filter: An Additional Edge Term

Same idea: weighted average of pixels.

$$BF[I]_p = \frac{1}{W_p} \sum_{q \in \mathcal{S}} G_{\sigma_s}(\|\mathbf{p} - \mathbf{q}\|) G_{\sigma_r}(|I_p - I_q|) I_q$$

new

not new

new

normalization factor


space weight

range weight

favor nearby pixels

favor similar pixels

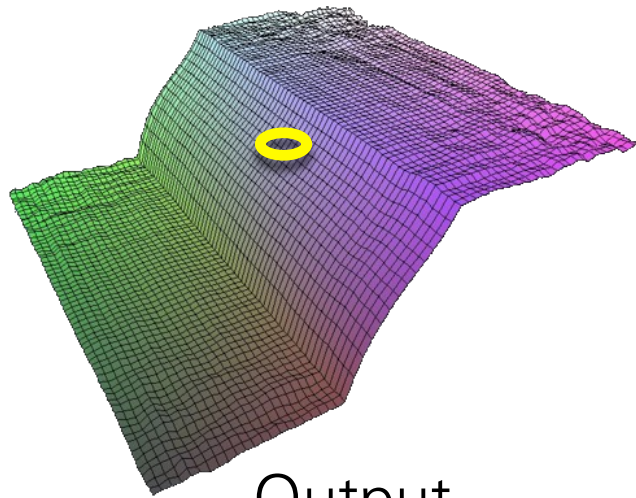
Space and Range Parameters

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


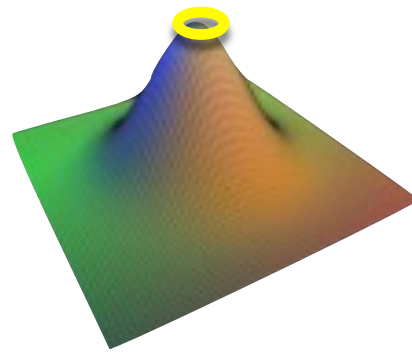
- space σ_s : spatial extent of the kernel, size of the considered neighborhood.
- range σ_r : “minimum” amplitude of an edge

Gaussian filtering visualization

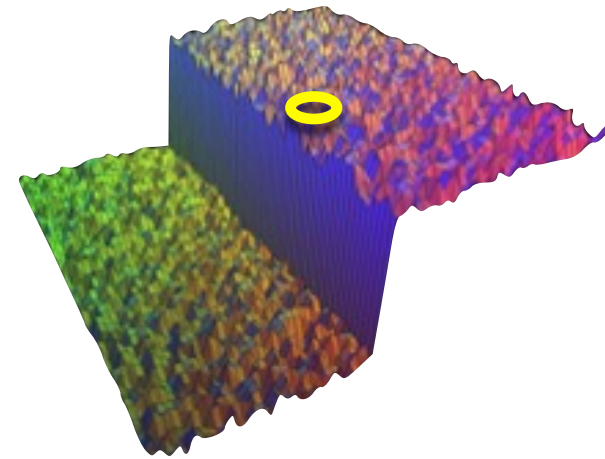
$$h[m, n] = \sum_{k, l} g[k, l] f[m + k, n + l]$$



Output



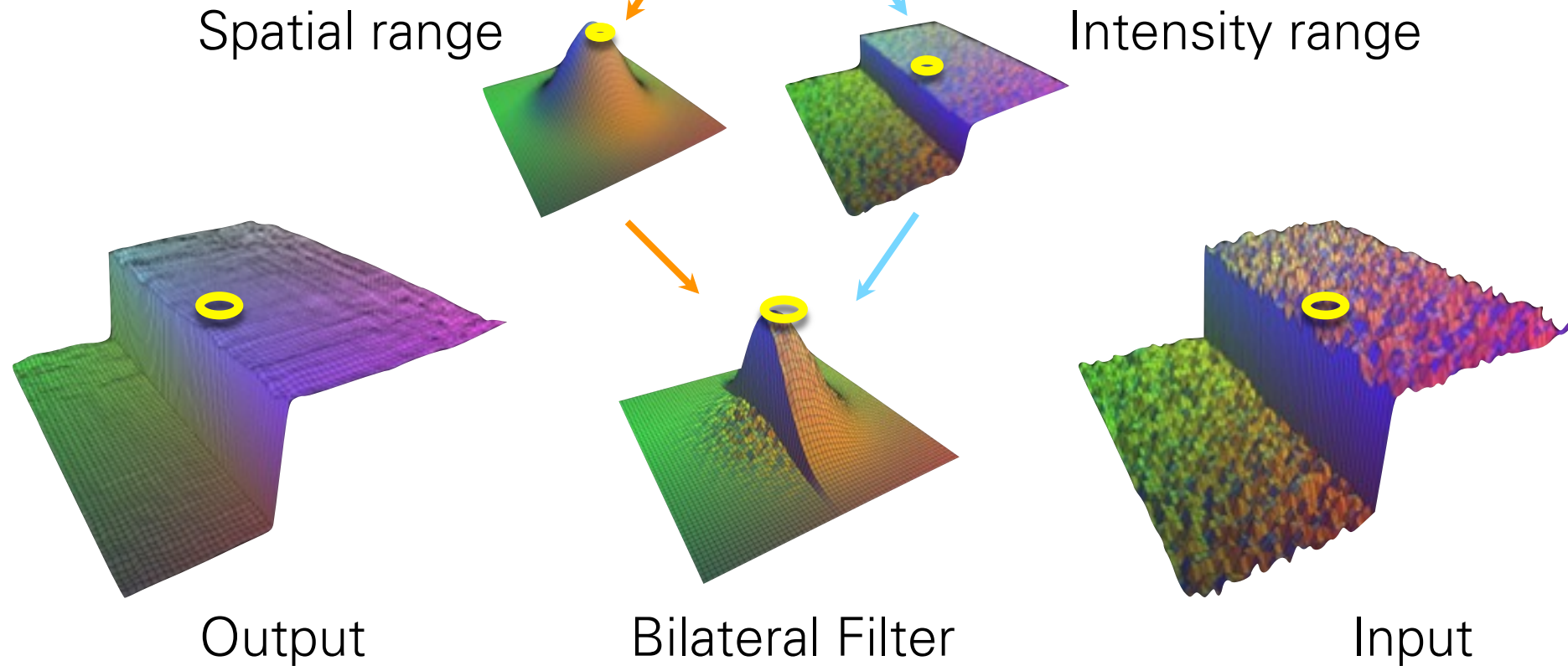
Gaussian Filter



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 Parameter Space



input

$\sigma_r = 0.1$

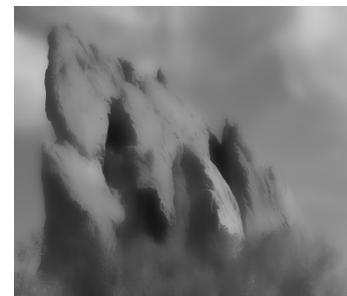
$\sigma_r = 0.25$

$\sigma_r = \infty$
(Gaussian blur)

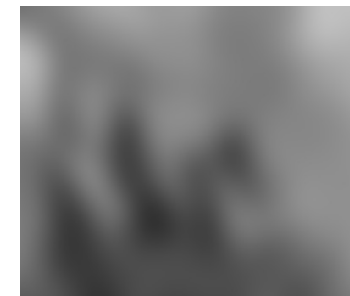
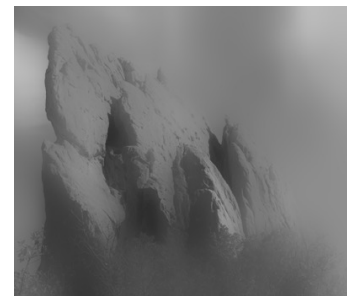
$\sigma_s = 2$



$\sigma_s = 6$



$\sigma_s = 18$



Bilateral Filtering Color Images

For gray-level images

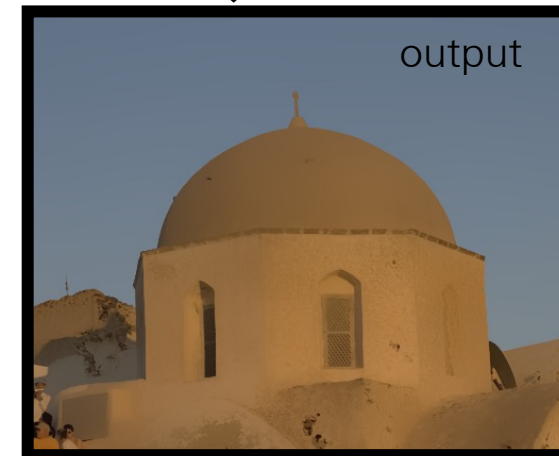
$$BF[I]_{\mathbf{p}} = \frac{1}{W_{\mathbf{p}}} \sum_{\mathbf{q} \in S} G_{\sigma_s}(\|\mathbf{p} - \mathbf{q}\|) G_{\sigma_r}(\|I_{\mathbf{p}} - I_{\mathbf{q}}\|) I_{\mathbf{q}}$$

intensity difference
scalar

For color images

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

color difference
3D vector
(RGB, Lab)

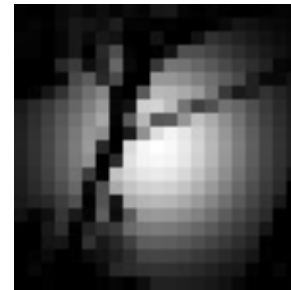
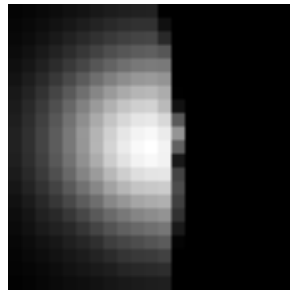
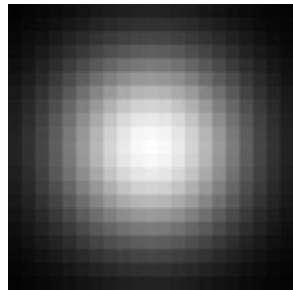


Hard to Compute

- Nonlinear

$$BF[I]_p = \frac{1}{W_p} \sum_{\mathbf{q} \in \mathcal{S}} G_{\sigma_s}(\|\mathbf{p} - \mathbf{q}\|) G_{\sigma_r}(|I_p - I_q|) I_q$$

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



- Brute-force implementation is slow > 10min

Additional Reading: S. Paris and F. Durand, A Fast Approximation of the Bilateral Filter using a Signal Processing Approach, In Proc. ECCV, 2006

Denoising



noisy input



bilateral filtering



median filtering

Contrast enhancement

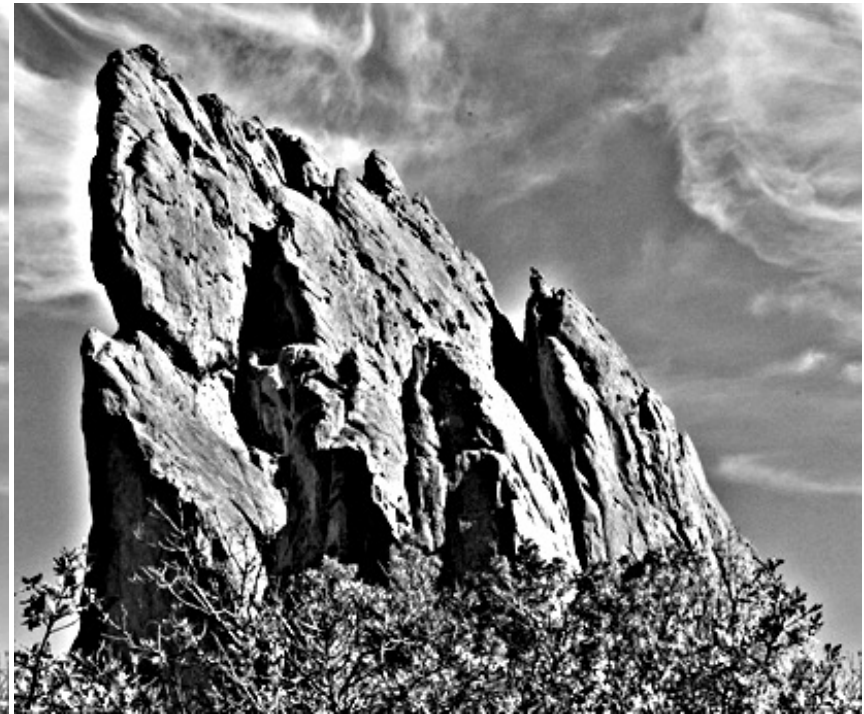
How would you use bilateral filtering for sharpening?



input



sharpening based on
bilateral filtering



sharpening based on
Gaussian filtering

Photo retouching



Photo retouching



original



digital pore removal (aka bilateral filtering)

Before



After



Close-up comparison



original



digital pore removal
(aka bilateral filtering)

Cartoonization

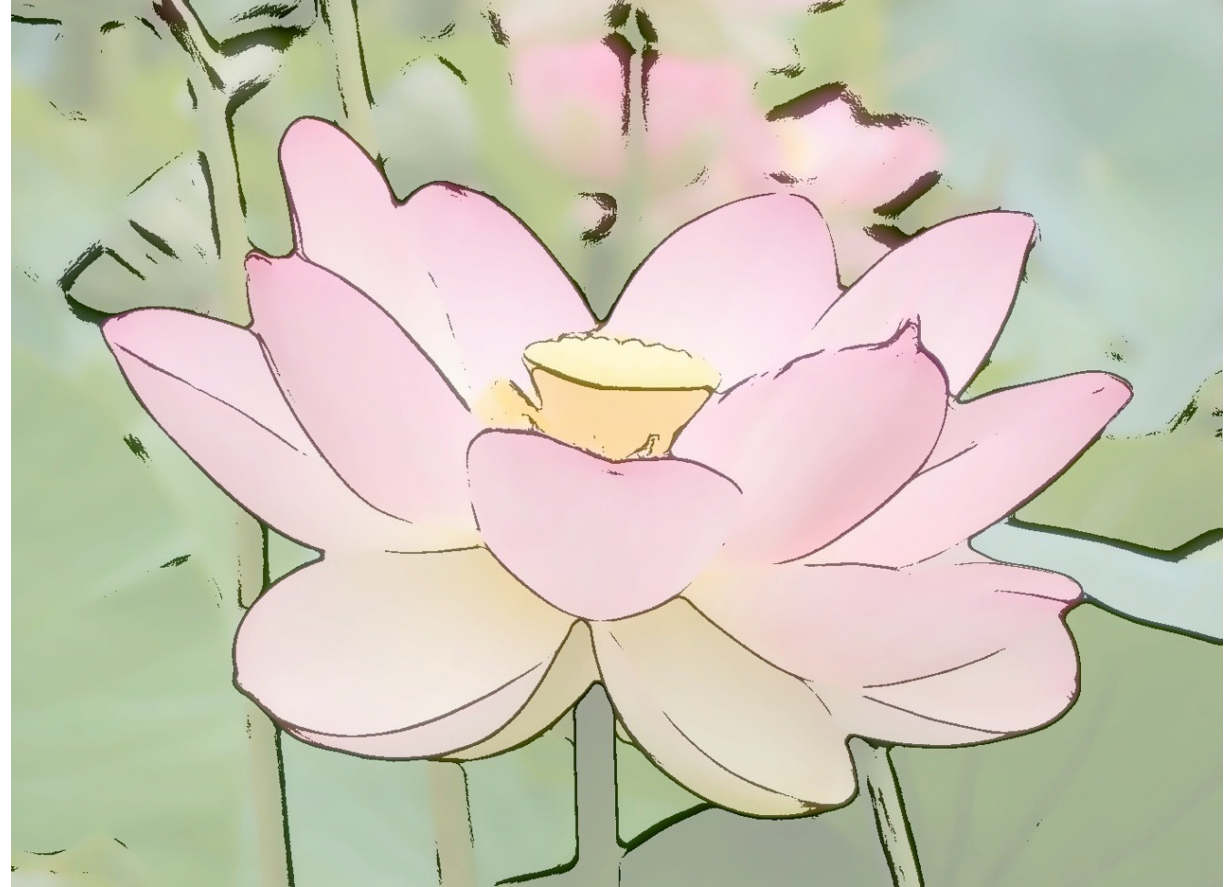


input



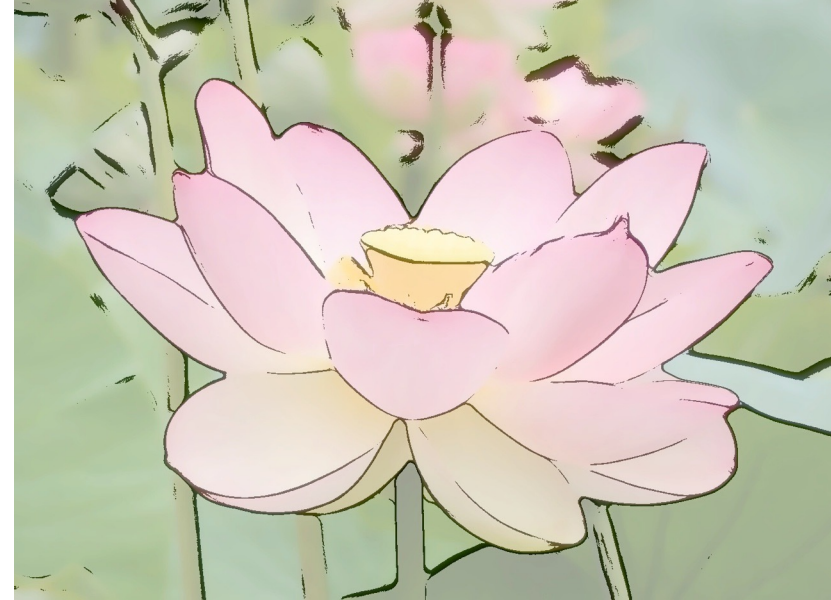
cartoon rendition

Cartoonization



How would you create this effect?

Cartoonization



edges from bilaterally filtered image

bilaterally filtered image

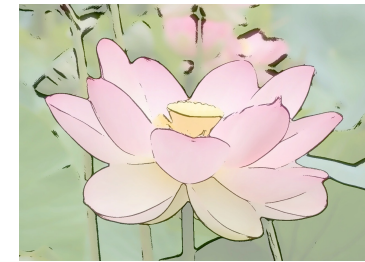
cartoon rendition



+



=



Note: image cartoonization and abstraction are very active research areas.

Is the bilateral filter:

Linear?

Shift-invariant?

Is the bilateral filter:

Linear?

- No.

Shift-invariant?

- No.

Does this have any bad implications?

The bilateral grid

Real-time Edge-Aware Image Processing with the Bilateral Grid

Jiawen Chen Sylvain Paris Frédo Durand

Computer Science and Artificial Intelligence Laboratory
Massachusetts Institute of Technology



Figure 1: The bilateral grid enables edge-aware image manipulations such as local tone mapping on high resolution images in real time. This 15 megapixel HDR panorama was tone mapped and locally refined using an edge-aware brush at 50 Hz. The process used about 1 MB of texture memory. The inset shows the original input.

Data structure for fast
edge-aware image
processing.

Flash/no-flash photography via bilateral filtering



Red Eye



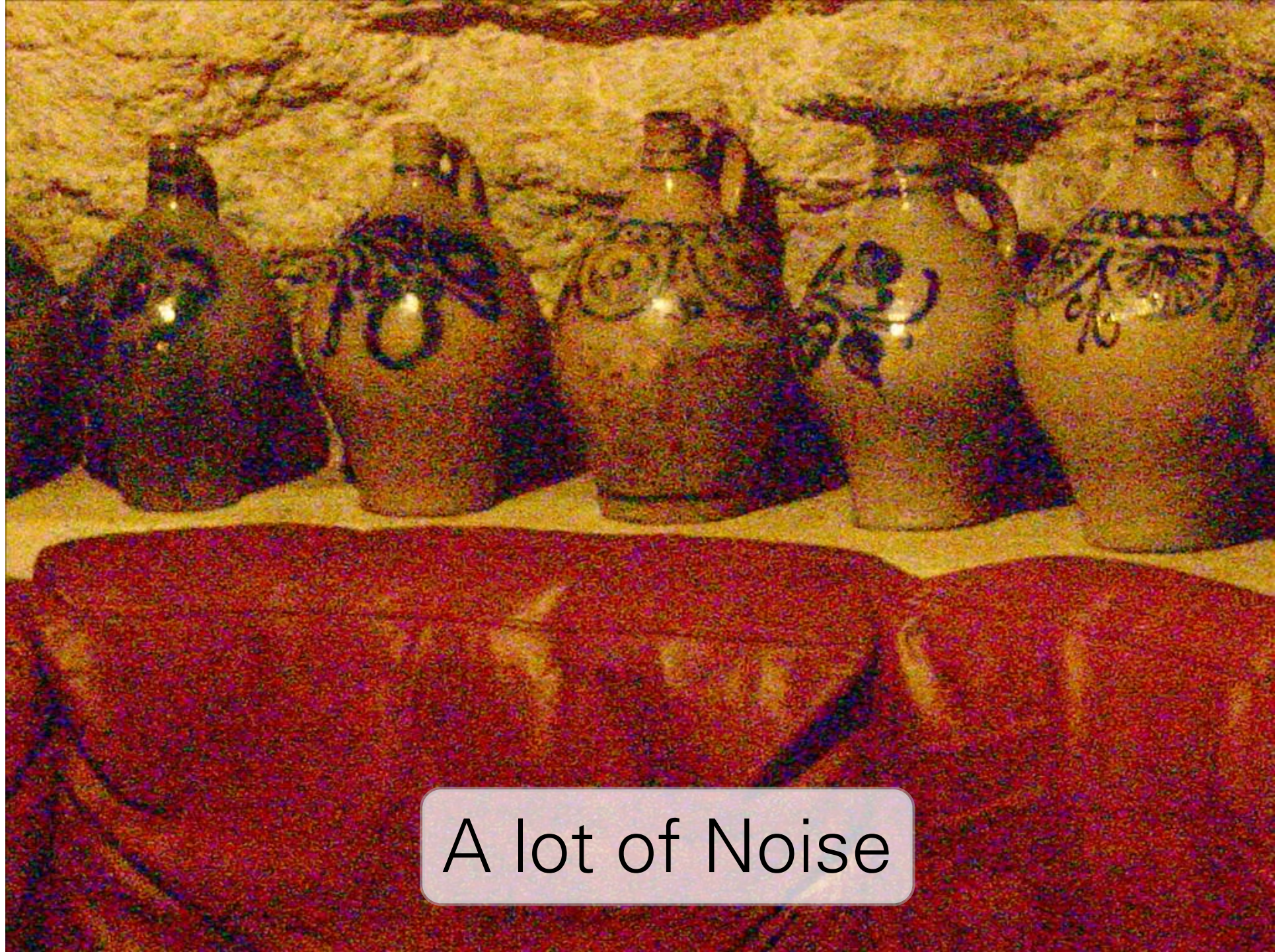
Unflattering Lighting



Motion Blur



Noise

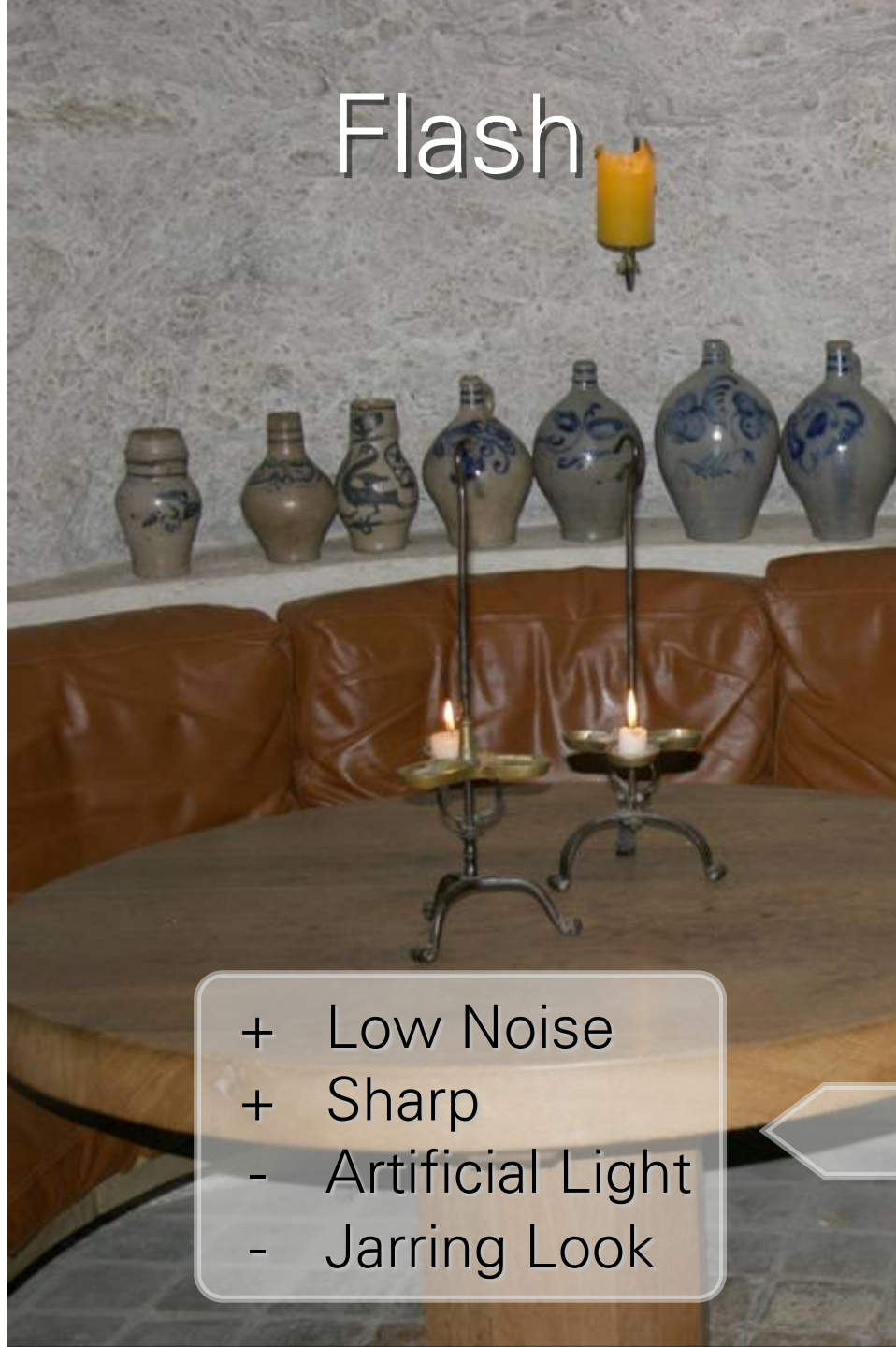


A lot of Noise



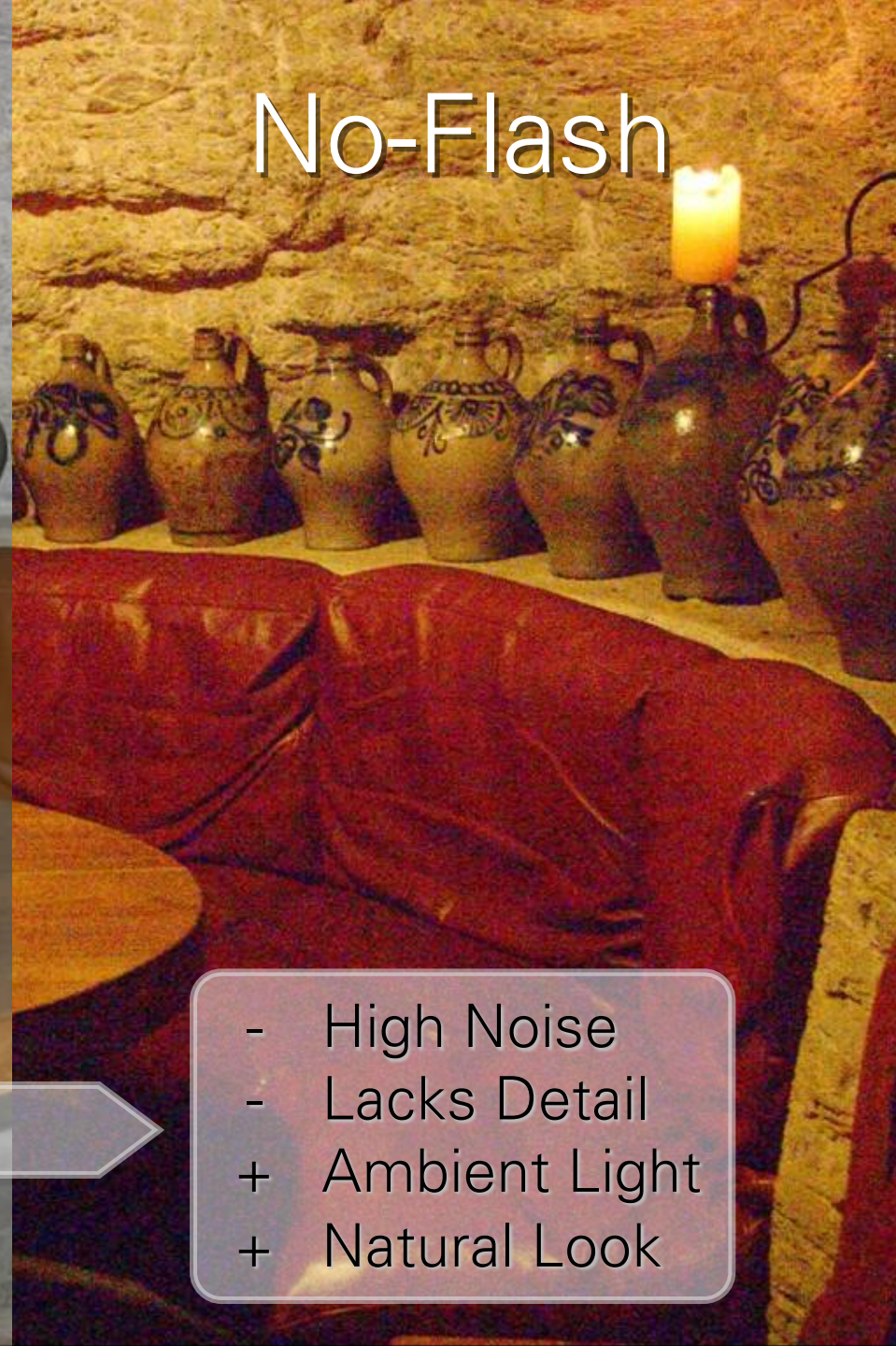
Ruined Ambiance

Flash



- + Low Noise
- + Sharp
- Artificial Light
- Jarring Look

No-Flash



- High Noise
- Lacks Detail
- + Ambient Light
- + Natural Look



Image acquisition



Image acquisition

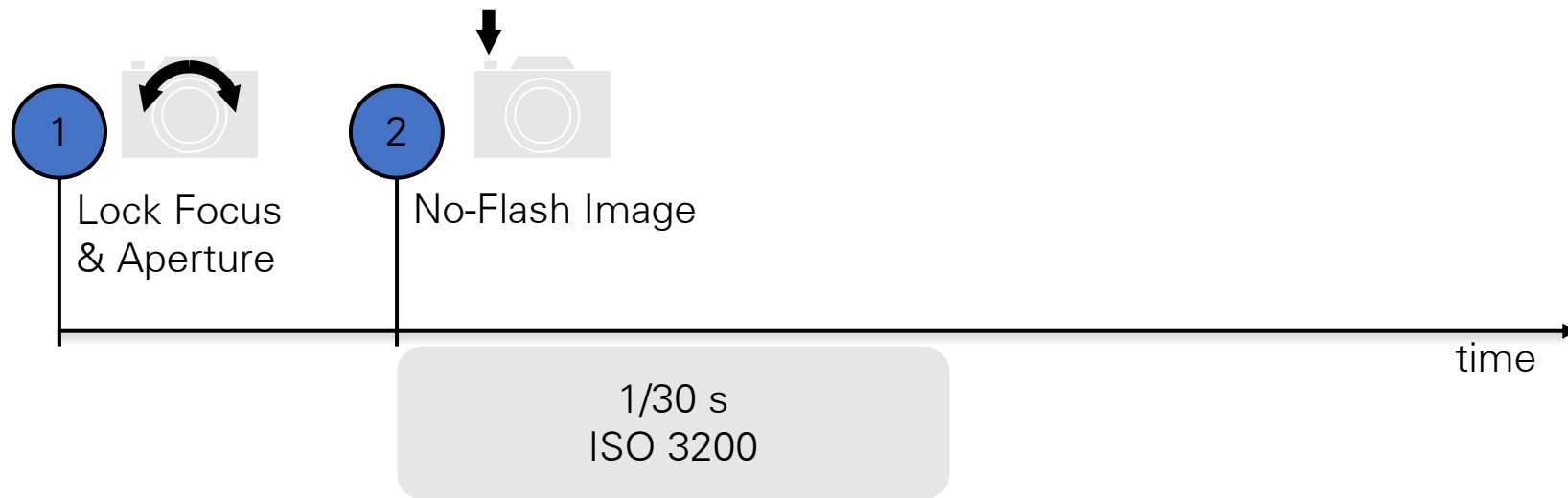
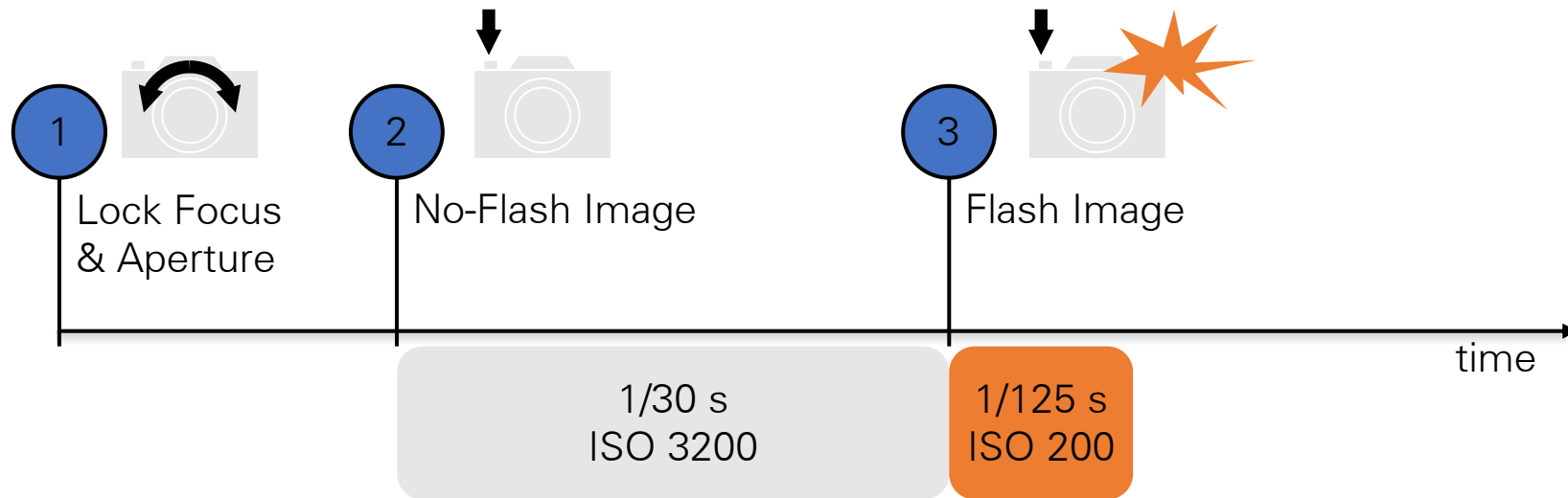


Image acquisition





Denoising Result



No-Flash



Denoising Result

Key idea

Denoise the no-flash image while maintaining the edge structure of the flash image

- How would you do this using the image editing techniques we've learned about?

Joint bilateral filtering

Denoising with bilateral filtering



noisy input



bilateral filtering



median filtering

Denoising with bilateral filtering

$$A_{p(col)}^{Base} = \frac{1}{k(p(col))} \sum_{p' \in \Omega} \overset{\text{spatial kernel}}{g_d(|p - p'|)} \underset{\text{intensity kernel}}{g_r(A_{p(col)} - A_{p'(col)})} A_{p'(col)}$$

- However, results still have noise or blur (or both)



Denoising with joint bilateral filtering

$$A_{p(col)}^{NR} = \frac{1}{k(p(col))} \sum_{p' \in \Omega} g_d(|p - p'|) g_r(\mathbf{F}_{p(col)} - \mathbf{F}_{p'(col)}) A_{p'(col)}$$

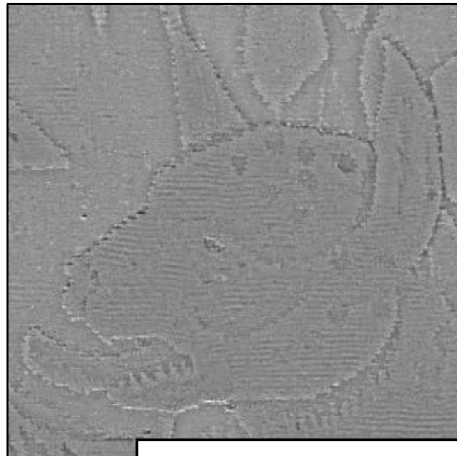
- In the flash image there are many more details
- Use the flash image F to find edges

Denoising with joint bilateral filtering

$$A_{p(col)}^{NR} = \frac{1}{k(p(col))} \sum_{p' \in \Omega} g_d(|p - p'|) g_r(\mathbf{F}_{p(col)} - \mathbf{F}_{p'(col)}) A_{p'(col)}$$



Bilateral filter



The difference



Joint Bilateral filter

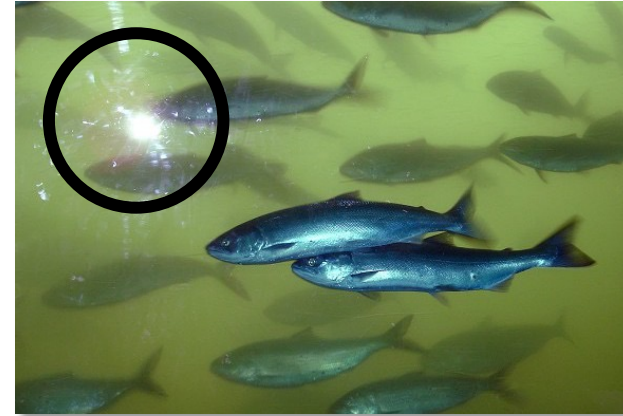
Not all edges in the flash image are real

Can you think of any types of edges that may exist in the flash image but not the ambient one?

Not all edges in the flash image are real



shadows



specularities

- May cause over- or under-blur in joint bilateral filter
- We need to eliminate their effect

Detecting shadows

- Observation: the pixels in the flash shadow should be similar to the ambient image.
- Not identical:
 1. Noise.
 2. Inter-reflected flash.

- Compute a shadow mask.
$$M^{Shad} = \begin{cases} 1 & \text{when } F^{Lin} - A^{Lin} \leq \tau_{Shad} \\ 0 & \text{otherwise.} \end{cases}$$

- Take pixel p if $F_{p(col)}^{Lin} - A_{p(col)}^{Lin} \leq \tau_{Shadow}$

- τ_{Shadow} is manually adjusted

- Mask is smoothed and dilated

Detecting specularities

- Take pixels where sensor input is close to maximum (very bright).
 - Over fixed threshold τ_{spec}
- Create a specular mask.
- Also smoothed.
- M – the combination of shadow and specular masks:

Where $M_p=1$, we use A^{Base} . For other pixels we use A^{NR} .

Detail transfer

- Denoising cannot add details missing in the ambient image
- Exist in flash image because of high SNR
- We use a quotient image:

$$F_{p(col)}^{Detail} = \frac{F_{p(col)} + \varepsilon}{F_{p(col)}^{Base} + \varepsilon}$$

Reduces the effect of noise in F

Bilateral filtered

- Multiply with A^{NR} to add the details
- Masked in the same way

Why does this quotient image make sense for detail?

Detail transfer

- Denoising cannot add details missing in the ambient image
- Exist in flash image because of high SNR
- We use a quotient image:

$$F^{Detail}_{p(col)} = \frac{F_{p(col)} + \varepsilon}{F^{Base}_{p(col)} + \varepsilon}$$

Reduces the effect of noise in F



Detail transfer

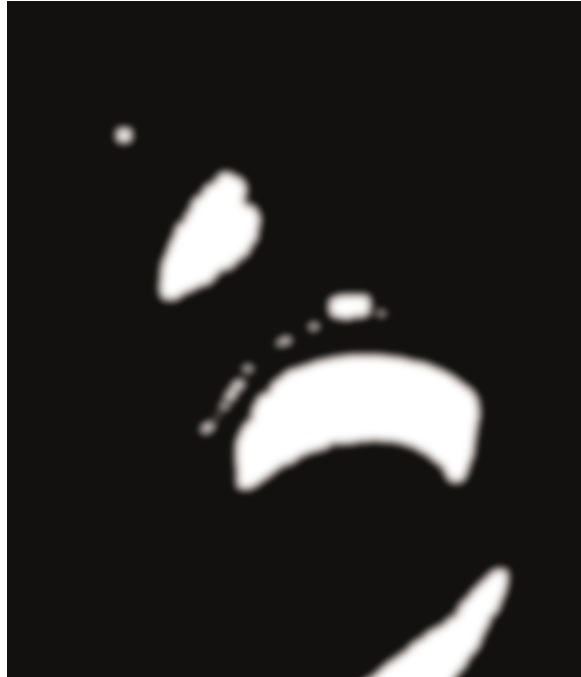


Orig. (top)

Detail Transfer (bottom)



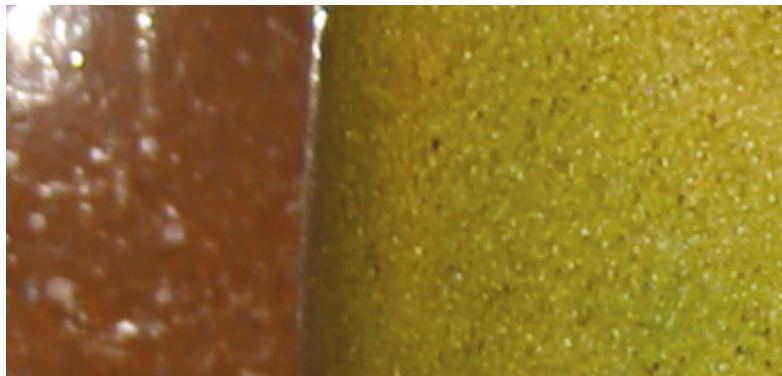
Detail Transfer w/o Mask



Shadow and Specularity Mask



Detail Transfer w/ Mask.



Flash

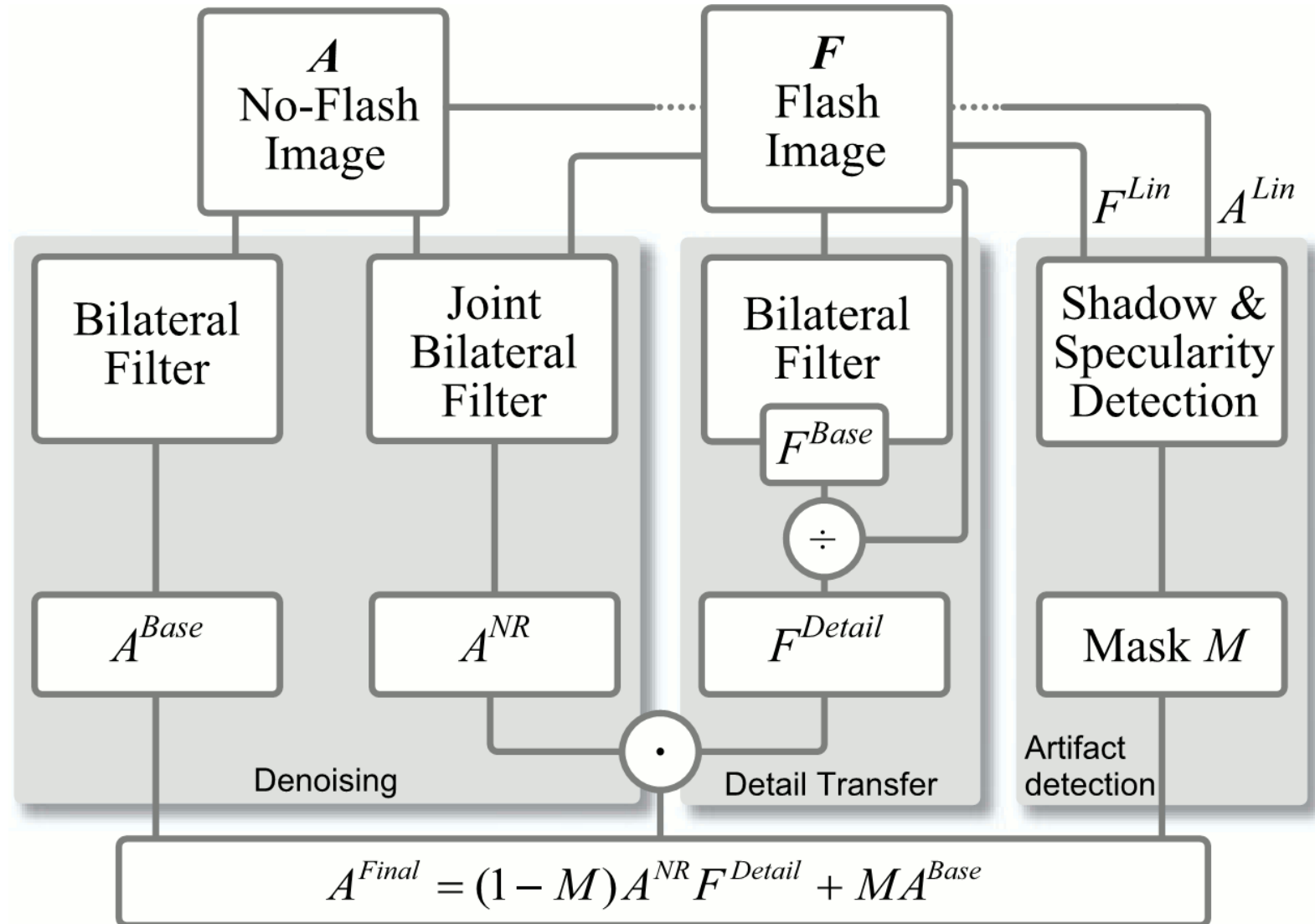


No-Flash



Detail Transfer w/ Denoising

Full pipeline



Demonstration



ambient-only



joint bilateral and detail transfer



Flash



No-Flash



No-Flash



Result



Flash



No-Flash



No-Flash



Result



Flash



No-Flash



Flash



No-Flash

Result

Joint bilateral filtering other applications

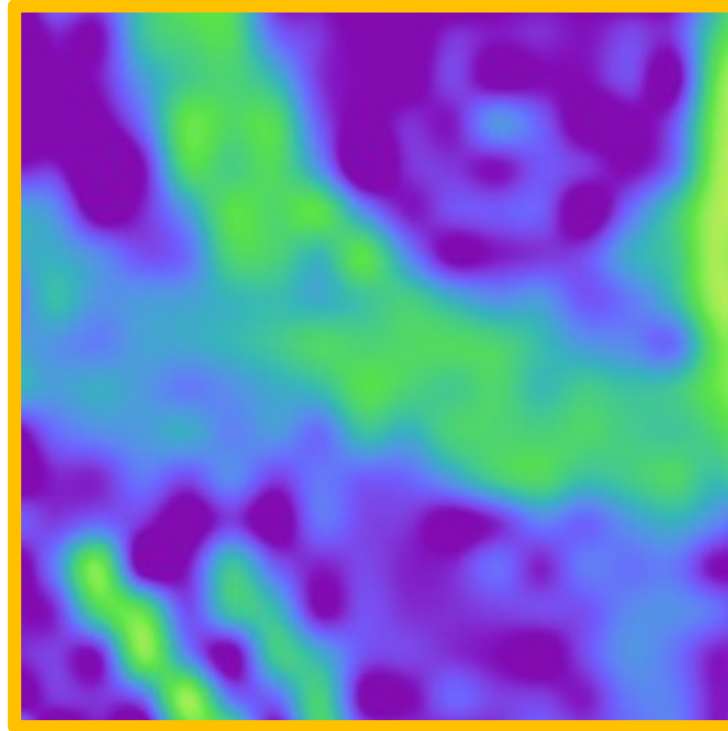
Edge-aware depth denoising

$$A_{p(col)} = \frac{1}{k(p(col))} \sum_{p' \in \Omega} g_d(|p - p'|) g_r(F_{p(col)} - F_{p'(col)}) A_{p'(col)}$$

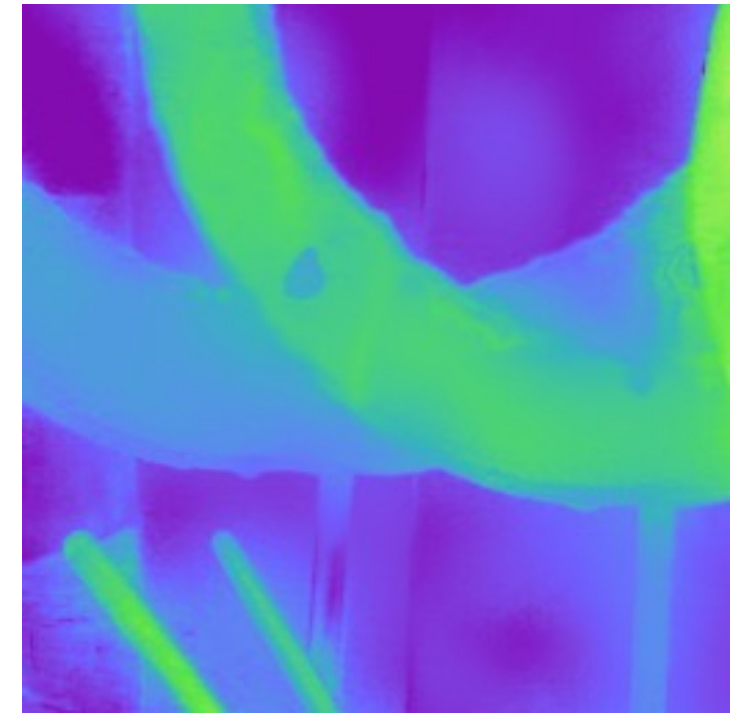
Use joint bilateral filtering, with the input image as guide.



One of two input images



Depth from disparity



Guided filtering

Other applications of joint bilateral filtering

Deep Bilateral Learning for Real-Time Image Enhancement

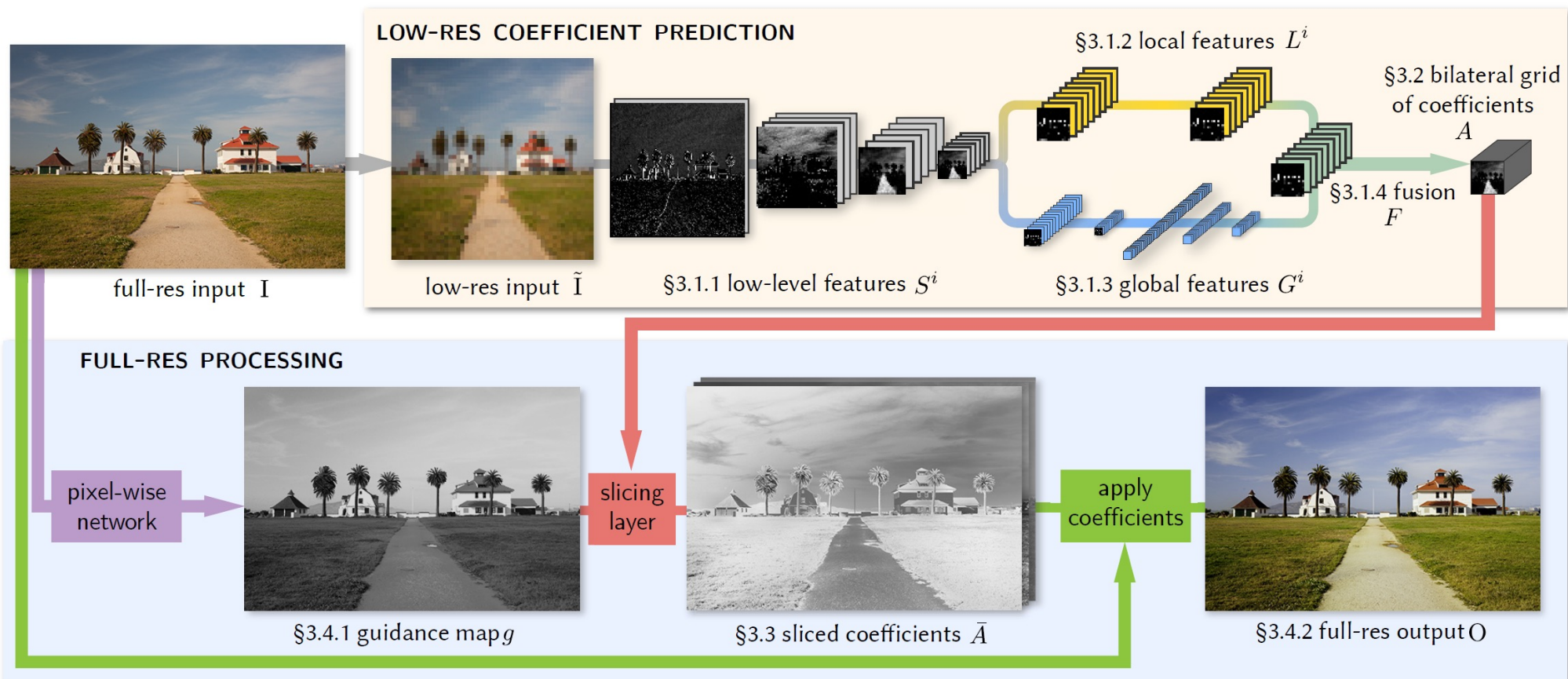
MICHAËL GHARBI, MIT CSAIL

JIAWEN CHEN, Google Research

JONATHAN T. BARRON, Google Research

SAMUEL W. HASINOFF, Google Research

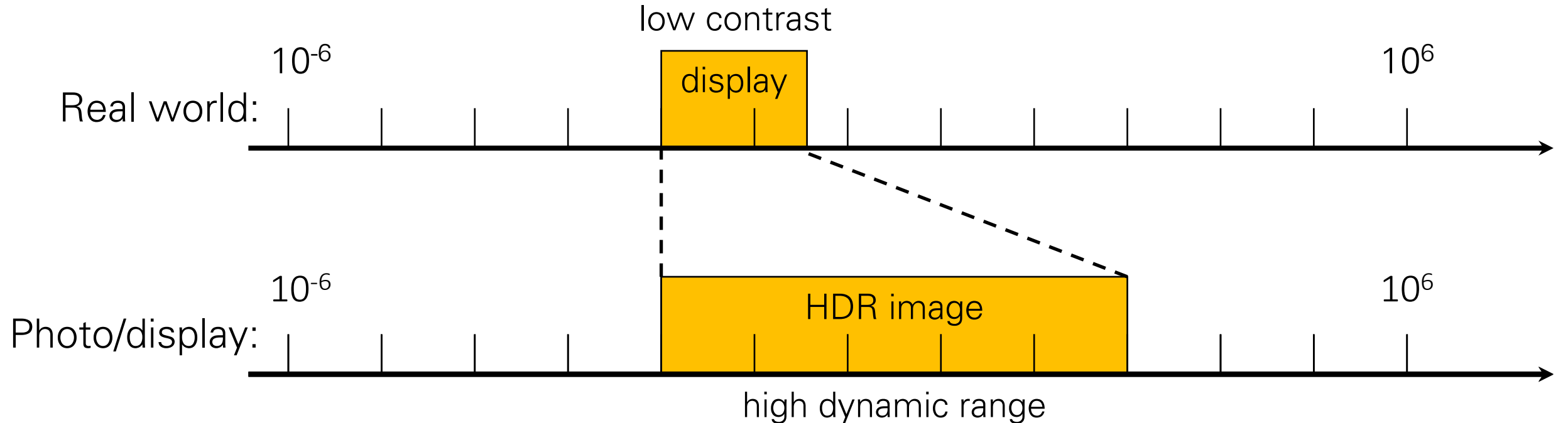
FRÉDO DURAND, MIT CSAIL / Inria, Université Côte d'Azur



Tonemapping via bilateral filtering

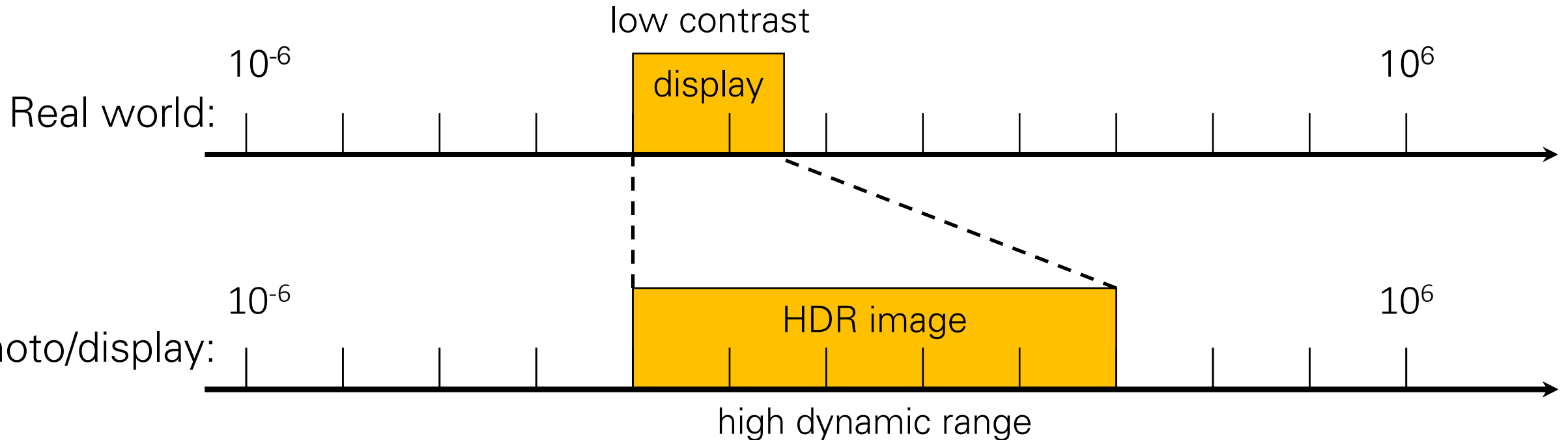
Display the information

- Recall our HDR class
- Match limited contrast of the medium while preserving details



Display the information

- Recall our HDR class
- Match limited contrast of the medium while preserving details



Tonemapping

Tonemapping

- Called tone mapping operators
- Two general categories:
 - Global (spatially invariant)
 - Local (spatially varying)

Tone mapping for very HDR scenes

- sun overexposed
- foreground too dark



Tone mapping for very HDR scenes

- Scene has $>100,000:1$ dynamic range, JPEG has 255:1
- How can we compress the scene's dynamic range?

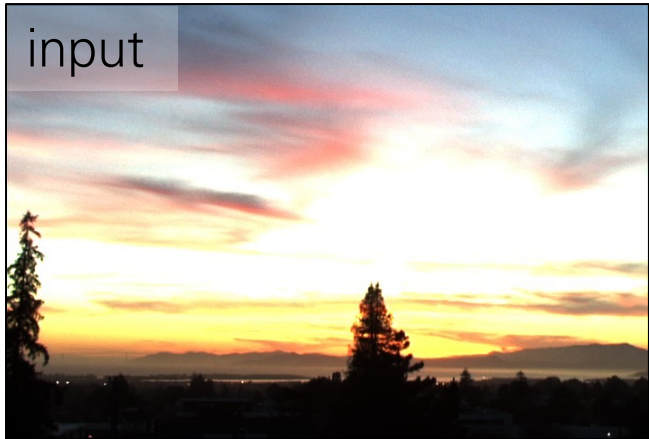


Tone mapping for very HDR scenes

- Scene has $>100,000:1$ dynamic range, JPEG has $255:1$
- How can we compress the scene's dynamic range?
- Scale linearly?
 - If we scaled linearly from $100,000:1$ to $255:1$, everything but the sun would be black!



Tonemapping w/ Simple Gamma



- gamma correction, applied independently on R, G, B:

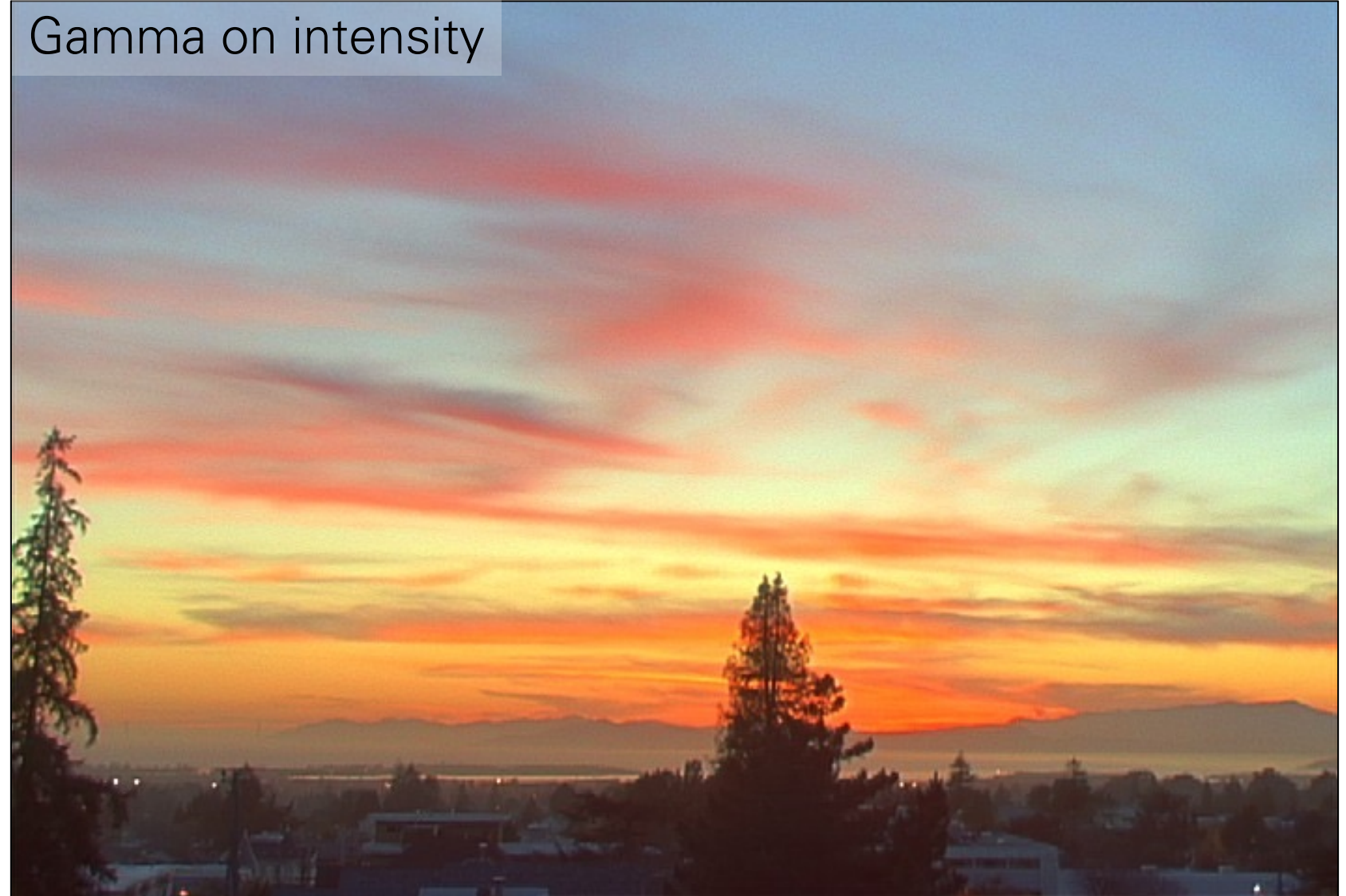
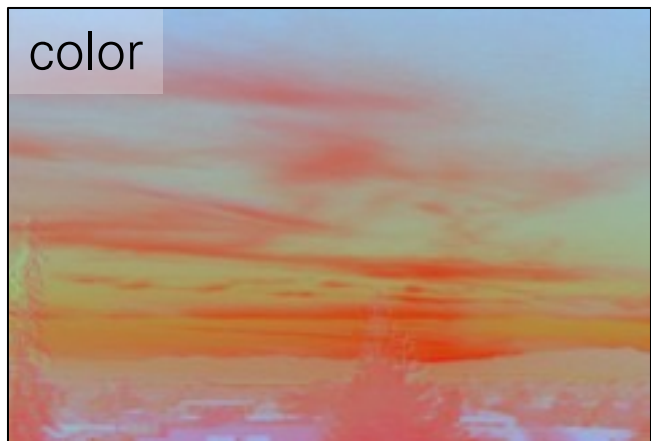
$$I = I^\gamma$$

- global tonemapping
- colors are washed out

Tonemapping w/ Simple Gamma

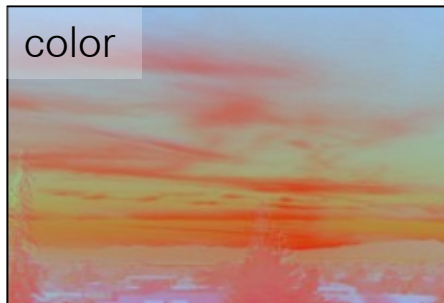
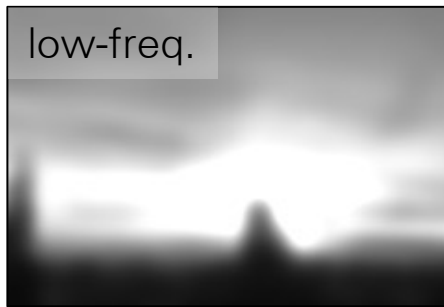


- gamma in intensity only!
- Intensity details lost



Oppenheim 1968, Chiu et al. 1993

- Reduce contrast of low-frequencies, preserve high frequencies

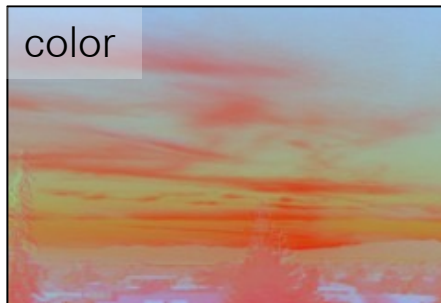
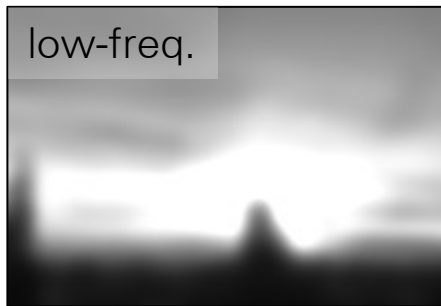


Reduce low frequency



The halo nightmare

- For strong edges; because they contain high frequency

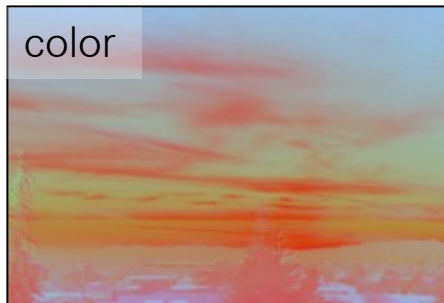
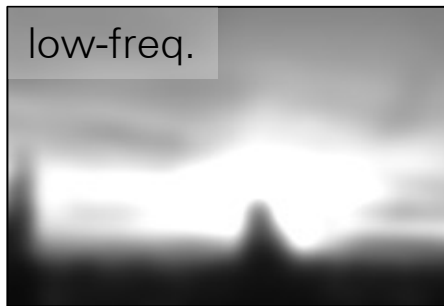


Reduce low frequency



The halo nightmare

- Similar to unsharp mask of luminance in log domain

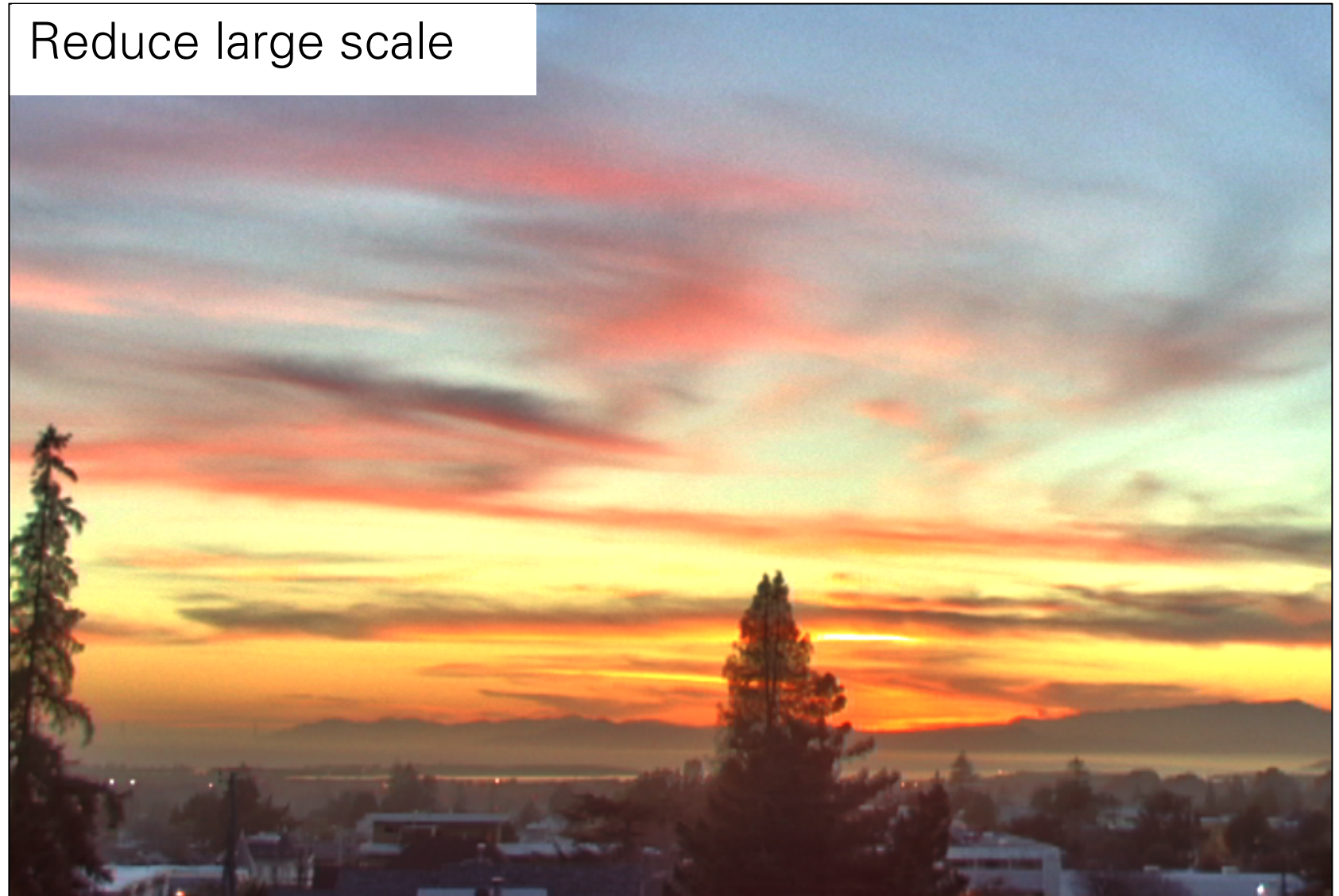
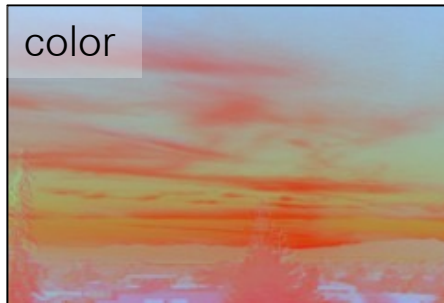
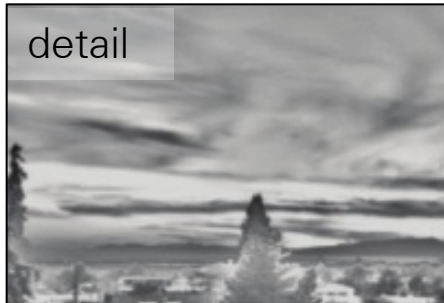
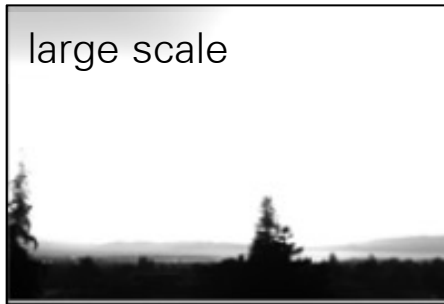


Reduce low frequency



Tonemapping w/ Bilateral Filter (Durand and Dorsey, 2002)

- Don't blur across edges, decompose using bilateral filter



Tonemapping w/ Bilateral Filter (Durand and Dorsey, 2002)

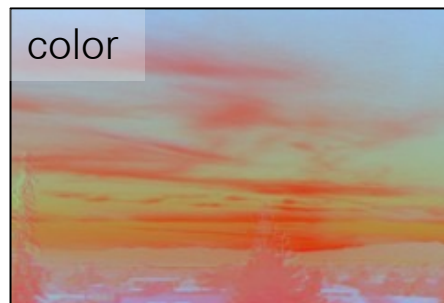


Contrast too high!

Tonemapping w/ Bilateral Filter (Durand and Dorsey, 2002)



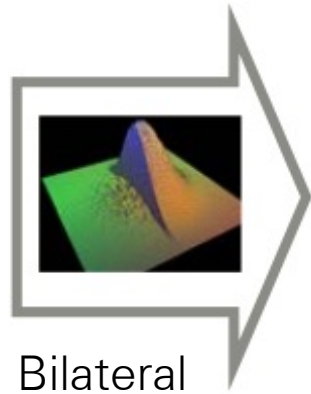
$$\text{Intensity} = 0.3R + 0.6G + 0.1B$$



$$\begin{aligned} R' &= R / \text{intensity} \\ G' &= G / \text{intensity} \\ B' &= B / \text{intensity} \end{aligned}$$

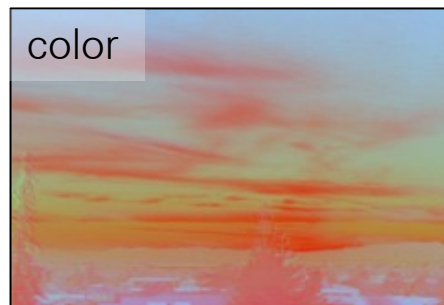
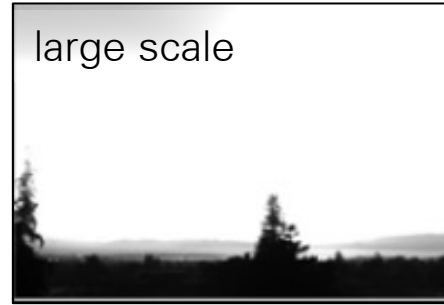
Important to use ratios
(makes it luminance
invariant)

Tonemapping w/ Bilateral Filter (Durand and Dorsey, 2002)



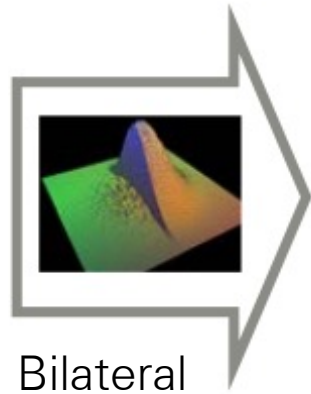
Bilateral
Filter

in log



Spatial sigma: 2-5% image size
Range sigma: 0.4 (in log 10)

Tonemapping w/ Bilateral Filter (Durand and Dorsey, 2002)

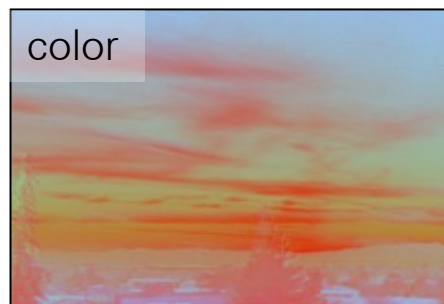


Bilateral
Filter

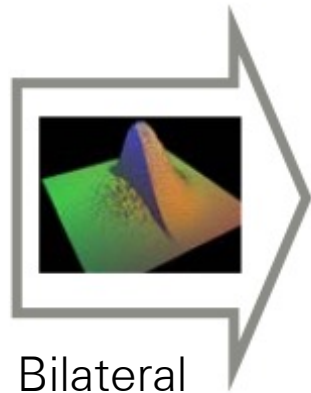
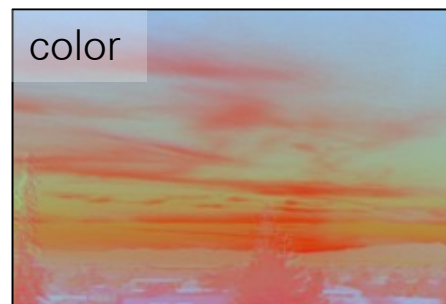
in log



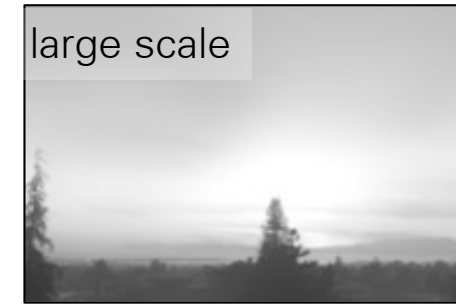
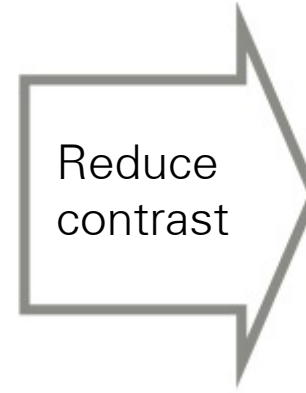
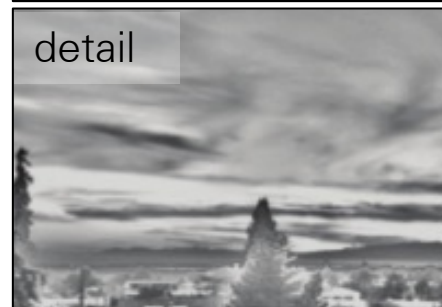
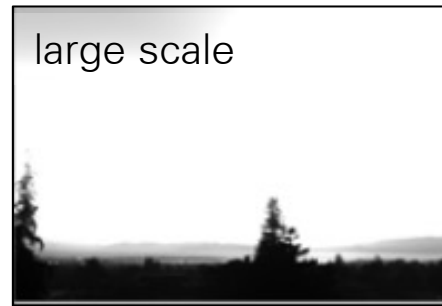
detail = log intensity - large scale
(residual)



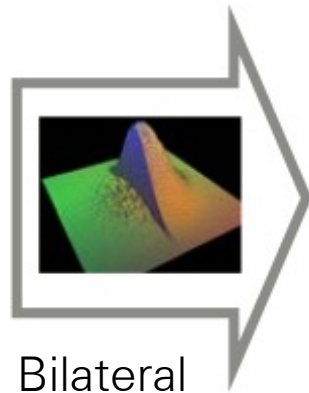
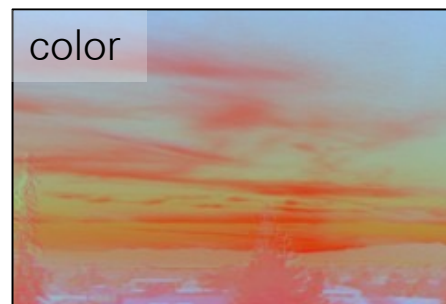
Tonemapping w/ Bilateral Filter (Durand and Dorsey, 2002)



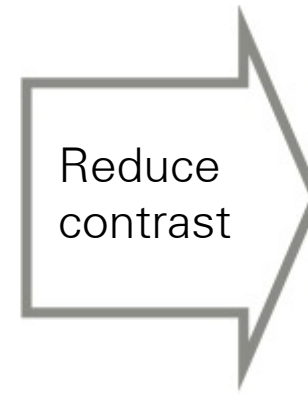
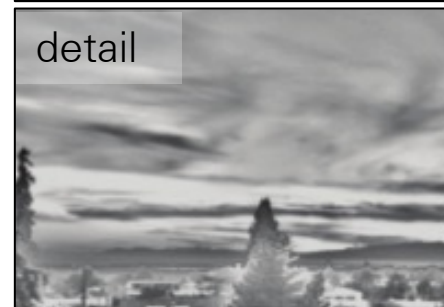
Bilateral
Filter
in log



Tonemapping w/ Bilateral Filter (Durand and Dorsey, 2002)



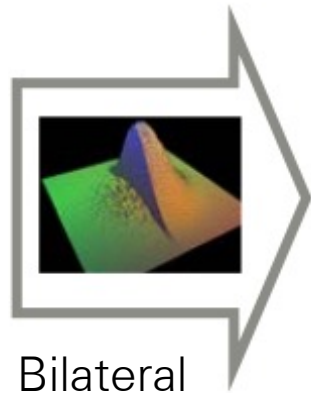
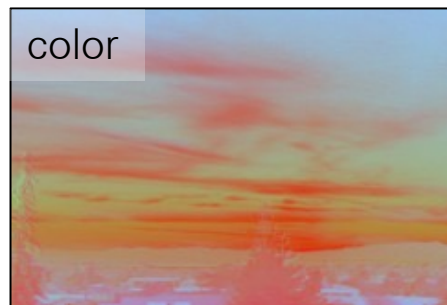
Bilateral Filter
in log



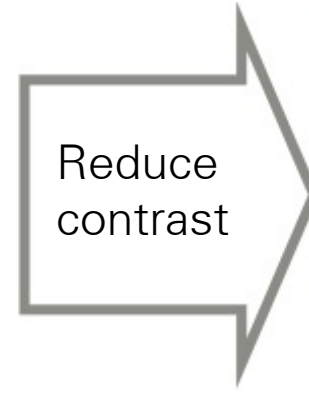
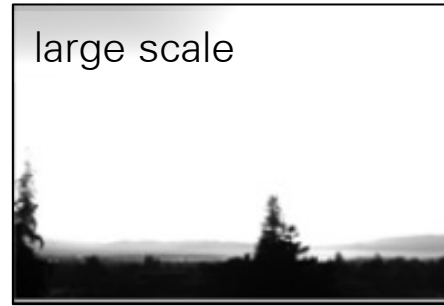
Preserve!



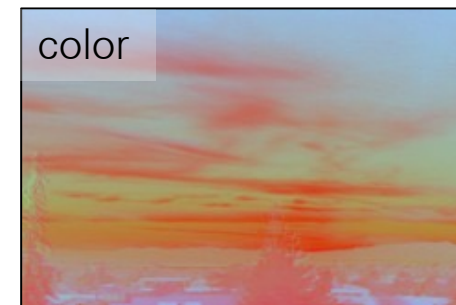
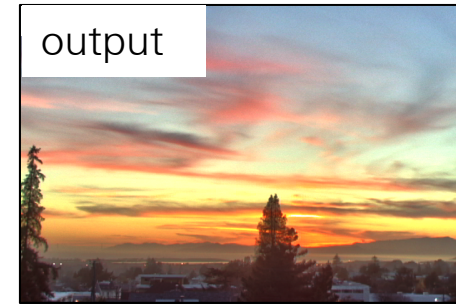
Tonemapping w/ Bilateral Filter (Durand and Dorsey, 2002)



Bilateral Filter
in log



Preserve!



Log domain

- Very important to work in the log domain
- Recall: humans are sensitive to multiplicative contrast
- With log domain, our notion of “strong edge” always corresponds to the same contrast

Scale decomposition in log domain

- $\text{inLog} = \log_{10}(\text{intensity})$
- $\text{inLogLarge} = \text{bilateralFilter}(\text{inLog})$
- $\text{inLogDetail} = \text{inLog} - \text{inLogLarge}$
- hence:
 - $\text{inLog} = \text{inLogDetail} + \text{inLogLarge}$, or
 - $\text{intensity} = 10^{\text{inLogDetail}} * 10^{\text{inLogLarge}}$
- Now manipulate large-scale and detail separately

Contrast reduction in log domain

$$\text{outLog} = \text{inLogDetail} + k * (\text{inLogLarge} - \max(\text{inLogLarge}))$$

- Normalize so that the biggest value is 0 in log
- Set target large-scale contrast (e.g. $\text{targetRange} = \log_{10}(100)$)
 - i.e. in **linear** output, we want 1:100 contrast for large scale
- Compute range of input's large-scale layer:
 - $\text{largeRange} = \max(\text{inLogLarge}) - \min(\text{inLogLarge})$
- Scale factor $k = \text{targetRange} / \text{largeRange}$

multiplication in log
=
γ exponent in linear

Contrast reduction in log domain

$$\text{outLog} = \text{detailAmp} * \text{inLogDetail} + k * (\text{inLogLarge} - \max(\text{inLogLarge}))$$

- Normalize so that the biggest value is 0 in log
- Set target large-scale contrast (e.g. $\text{targetRange} = \log_{10}(100)$)
 - i.e. in **linear** output, we want 1:100 contrast for large scale
- Compute range of input's large-scale layer:
 - $\text{largeRange} = \max(\text{inLogLarge}) - \min(\text{inLogLarge})$
- Scale factor $k = \text{targetRange} / \text{largeRange}$
- **Optional:** amplify detail by detailAmp

Contrast reduction in log domain

$$\text{outLog} = \text{detailAmp} * \text{inLogDetail} + k * (\text{inLogLarge} - \max(\text{inLogLarge}))$$

- $\text{outIntensity} = 10^{\text{outLog}}$
- Recall that R', G', B' is the intensity-normalized RGB color
 - $\text{outR} = \text{outIntensity} * R'$
 - $\text{outG} = \text{outIntensity} * G'$
 - $\text{outB} = \text{outIntensity} * B'$

What matters

- Spatial sigma: not very important
- Range sigma: quite important
- Use of the log domain for range: **critical**
 - Because HDR and because perception sensitive to multiplicative contrast

Modern edge-aware filtering: domain transform

Domain Transform for Edge-Aware Image and Video Processing

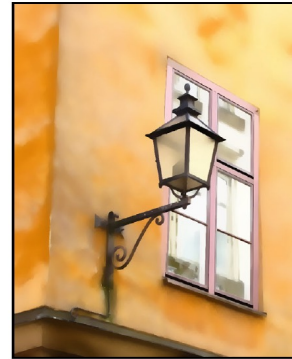
Eduardo S. L. Gastal*

Manuel M. Oliveira†

Instituto de Informática – UFRGS



(a) *Photograph*



(b) *Edge-aware smoothing*



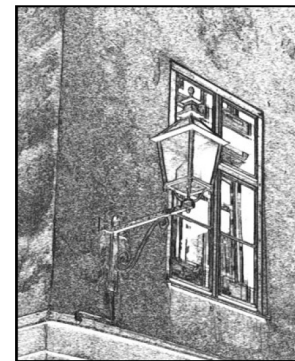
(c) *Detail enhancement*



(d) *Stylization*



(e) *Recoloring*



(f) *Pencil drawing*



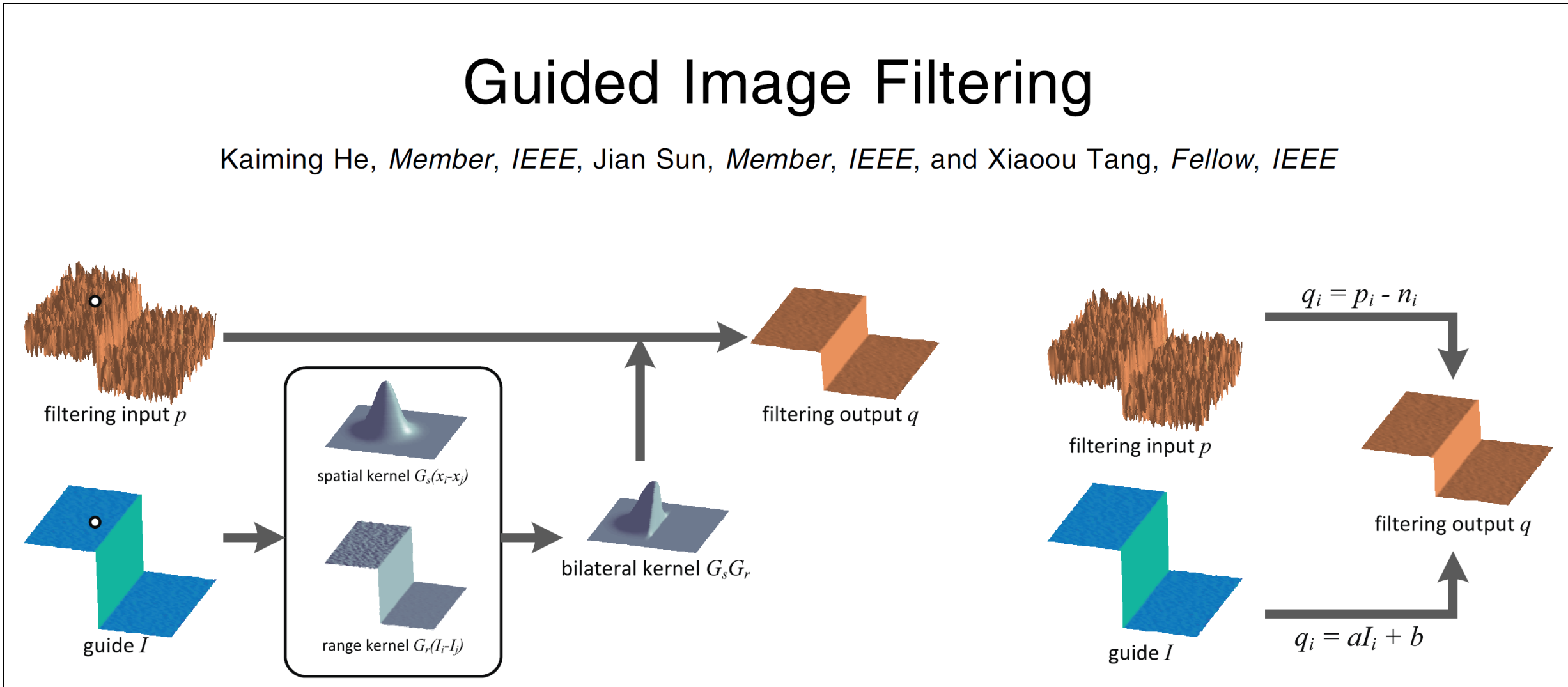
(g) *Depth-of-field*

Lots of great examples at: <https://www.inf.ufrgs.br/~eslgastal/DomainTransform/>

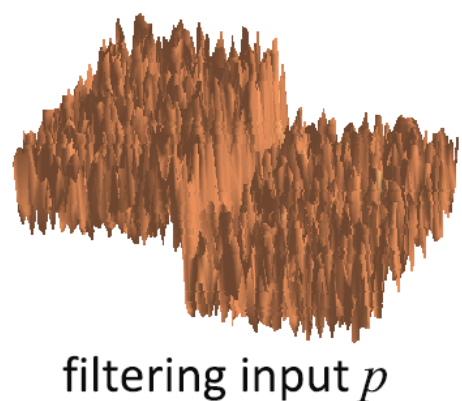
Modern edge-aware filtering: guided filter

Guided Image Filtering

Kaiming He, *Member, IEEE*, Jian Sun, *Member, IEEE*, and Xiaoou Tang, *Fellow, IEEE*

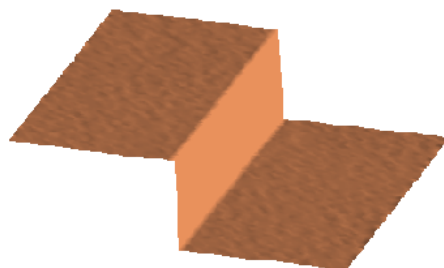


Guided Image Filtering



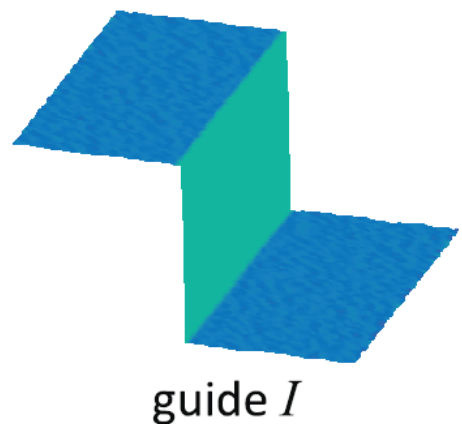
$$q_i = p_i - n_i$$

n_i : noise / texture



$$\nabla q_i = a \nabla I_i$$

$$q_i = a I_i + b$$



Bilateral/joint bilateral filter does not have this linear model

minimize $E(a_k, b_k) = \sum_{i \in \omega_k} ((a_k I_i + b_k - p_i)^2 + \epsilon a_k^2)$

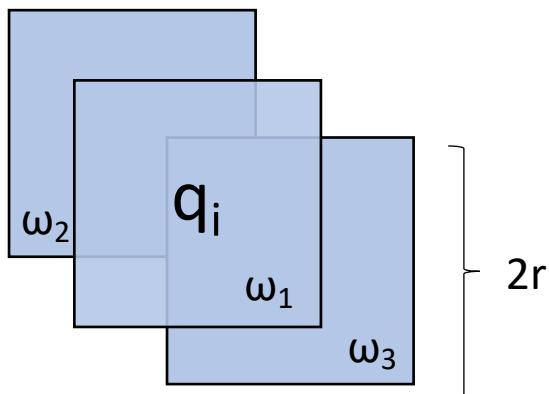
Linear regression

$$a_k = \frac{\frac{1}{|\omega|} \sum_{i \in \omega_k} I_i p_i - \mu_k \bar{p}_k}{\sigma_k^2 + \epsilon},$$

$$b_k = \bar{p}_k - a_k \mu_k.$$

Guided Image Filtering

- Extend to the entire image
 - In all local windows ω_k , compute the linear coefficients
 - Compute the average of $a_k I_i + b_k$ in all ω_k that covers pixel q_i



Definition

$$a_k = \frac{\frac{1}{|\omega|} \sum_{i \in \omega_k} I_i p_i - \mu_k \bar{p}_k}{\sigma_k^2 + \epsilon},$$

$$b_k = \bar{p}_k - a_k \mu_k.$$

$$q_i = \frac{1}{|\omega|} \sum_{k|i \in \omega_k} (a_k I_i + b_k)$$

Algorithm 1. Guided Filter.

Input: filtering input image p , guidance image I , radius r , regularization ϵ

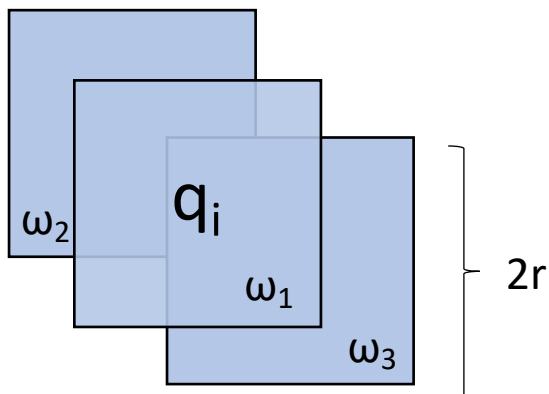
Output: filtering output q .

- 1: $\text{mean}_I = f_{\text{mean}}(I)$
 $\text{mean}_p = f_{\text{mean}}(p)$
 $\text{corr}_I = f_{\text{mean}}(I * I)$
 $\text{corr}_{Ip} = f_{\text{mean}}(I * p)$
- 2: $\text{var}_I = \text{corr}_I - \text{mean}_I * \text{mean}_I$
 $\text{cov}_{Ip} = \text{corr}_{Ip} - \text{mean}_I * \text{mean}_p$
- 3: $a = \text{cov}_{Ip} / (\text{var}_I + \epsilon)$
 $b = \text{mean}_p - a * \text{mean}_I$
- 4: $\text{mean}_a = f_{\text{mean}}(a)$
 $\text{mean}_b = f_{\text{mean}}(b)$
- 5: $q = \text{mean}_a * I + \text{mean}_b$

/* f_{mean} is a mean filter with a wide variety of $O(N)$ time methods. */

Guided Image Filtering

- Edge-preserving filter
- O(1) time, fast, accurate
- Gradient preserving
- Parameters
 - Window radius r
 - Regularization ϵ



Definition

$$a_k = \frac{\frac{1}{|\omega|} \sum_{i \in \omega_k} I_i p_i - \mu_k \bar{p}_k}{\sigma_k^2 + \epsilon},$$

$$b_k = \bar{p}_k - a_k \mu_k.$$

$$q_i = \frac{1}{|\omega|} \sum_{k|i \in \omega_k} (a_k I_i + b_k)$$

Algorithm 1. Guided Filter.

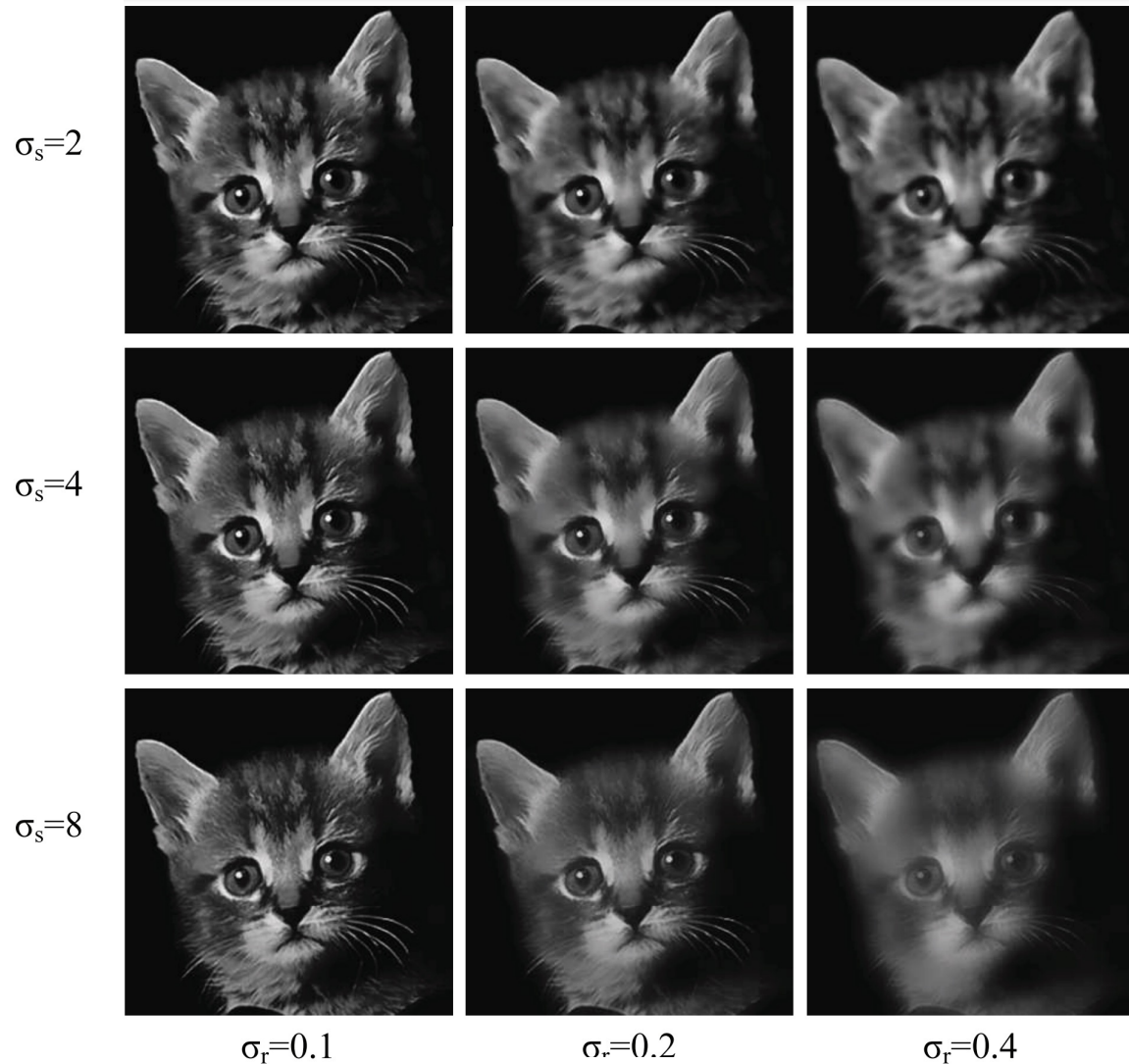
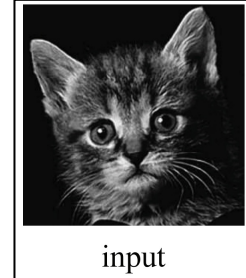
Input: filtering input image p , guidance image I , radius r , regularization ϵ

Output: filtering output q .

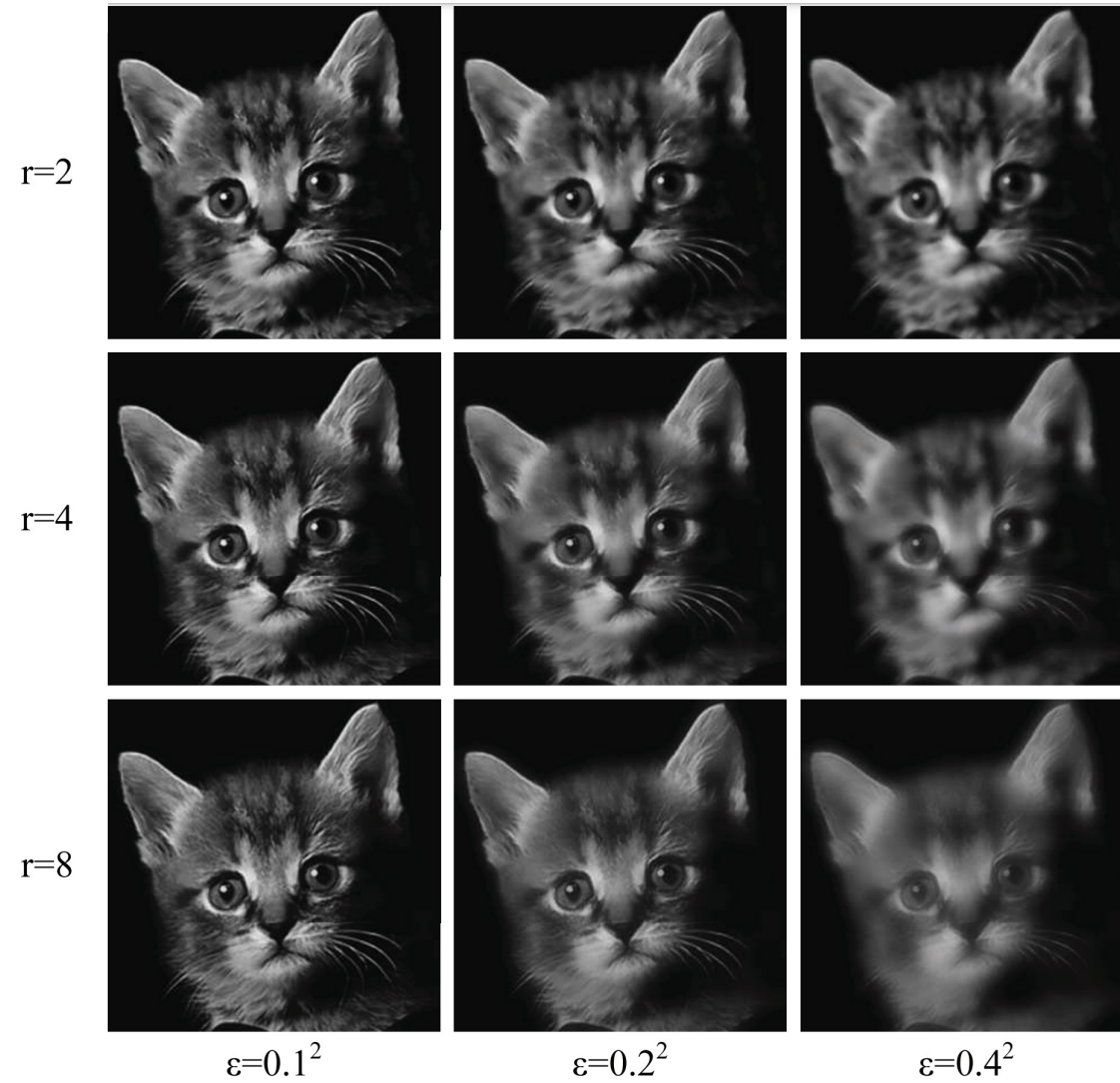
- 1: $\text{mean}_I = f_{\text{mean}}(I)$
 $\text{mean}_p = f_{\text{mean}}(p)$
 $\text{corr}_I = f_{\text{mean}}(I * I)$
 $\text{corr}_{Ip} = f_{\text{mean}}(I * p)$
- 2: $\text{var}_I = \text{corr}_I - \text{mean}_I * \text{mean}_I$
 $\text{cov}_{Ip} = \text{corr}_{Ip} - \text{mean}_I * \text{mean}_p$
- 3: $a = \text{cov}_{Ip} ./ (\text{var}_I + \epsilon)$
 $b = \text{mean}_p - a * \text{mean}_I$
- 4: $\text{mean}_a = f_{\text{mean}}(a)$
 $\text{mean}_b = f_{\text{mean}}(b)$
- 5: $q = \text{mean}_a * I + \text{mean}_b$

/* f_{mean} is a mean filter with a wide variety of O(N) time methods. */

Example: Edge-Preserving Smoothing



Bilateral Filter



Guided Filter

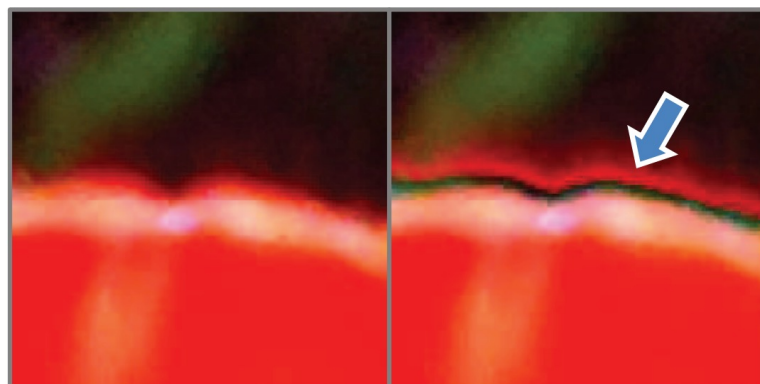
Example: Detail Enhancement



Original

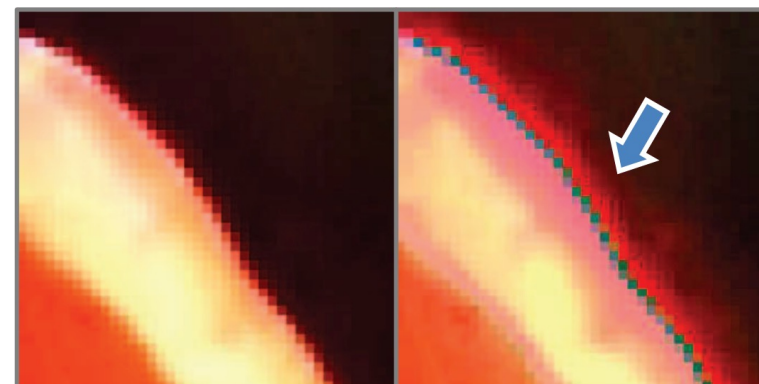
Guided Filter

Bilateral Filter



GF

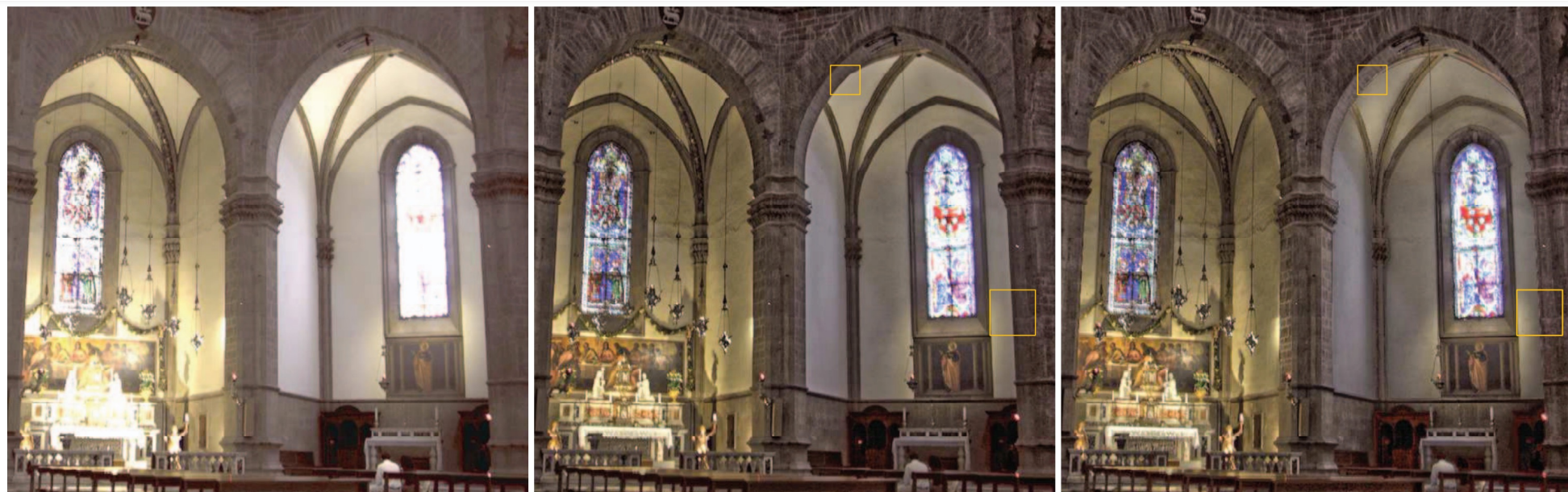
BF



GF

BF

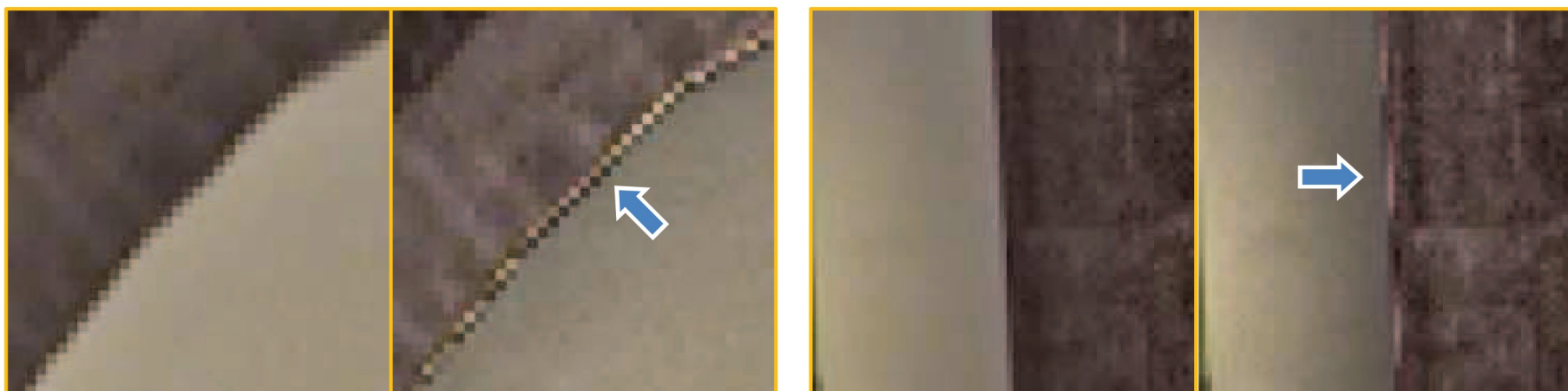
Example: Tonemapping



Original HDR

Guided Filter

Bilateral Filter



GF

BF

GF

BF

Example: Flash/No-Flash Photography



Guidance I



Guided Filter



Filter Input p

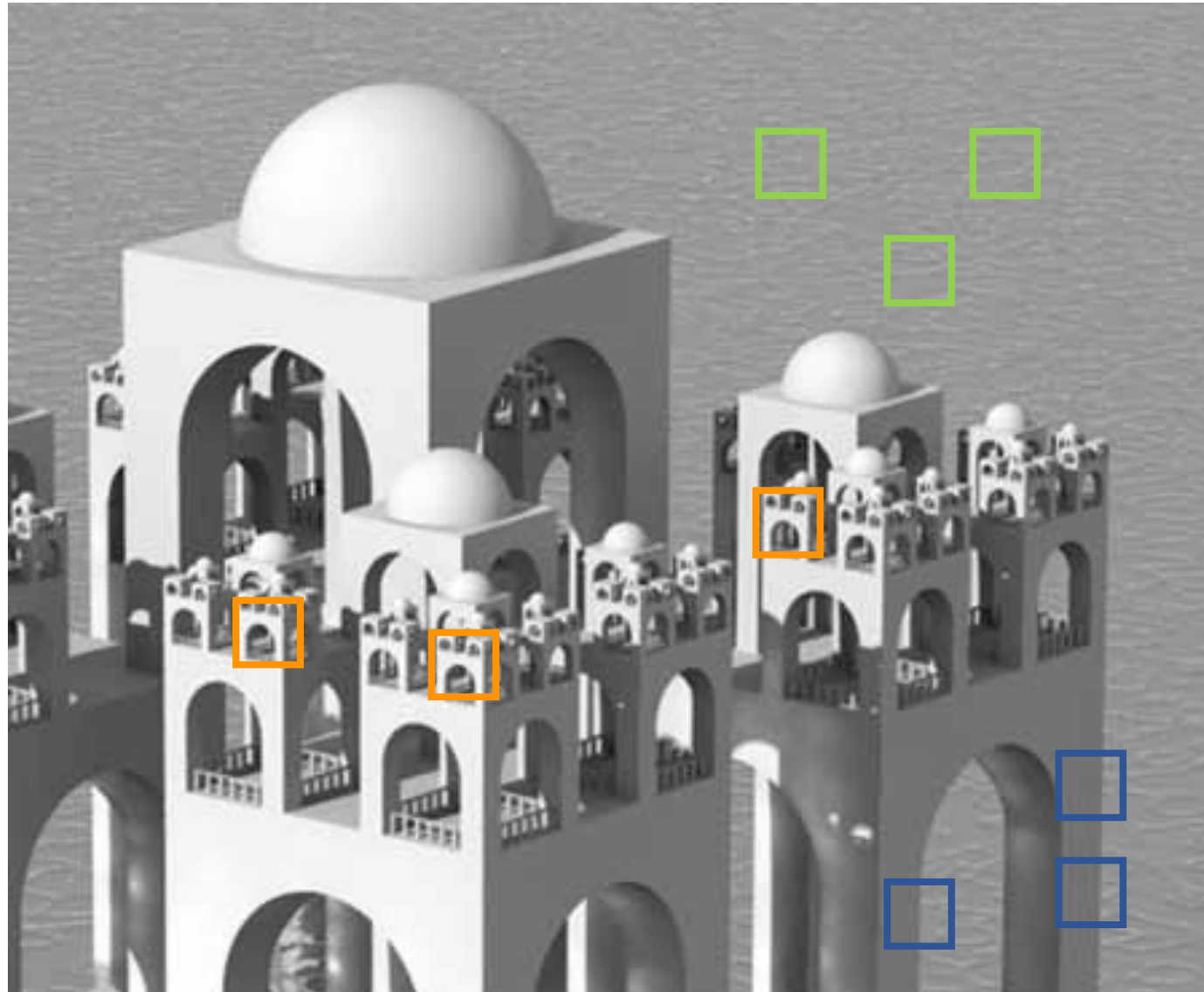


Joint Bilateral Filter



Non-Local Means Filter

Redundancy in natural images

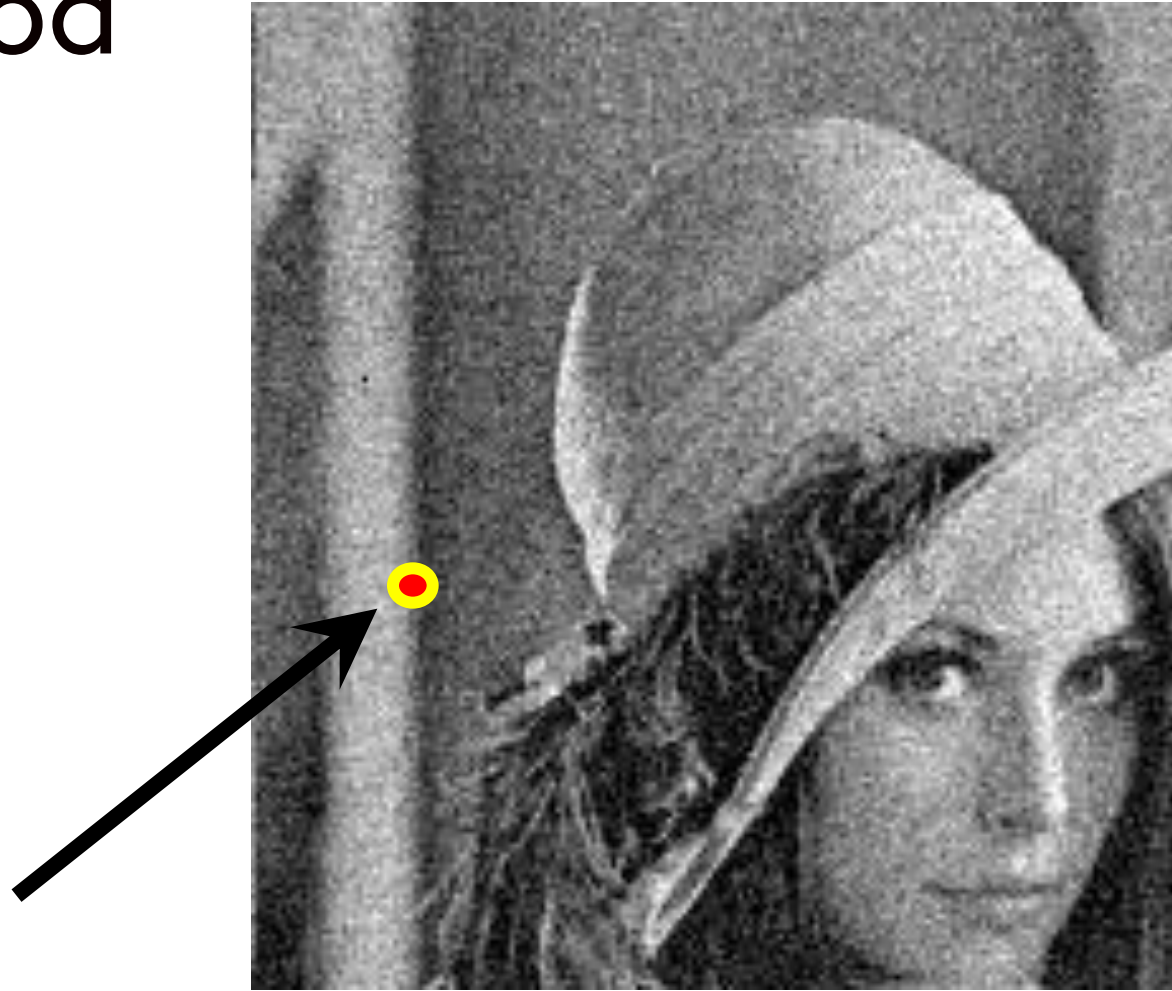


NL-Means Filter (Buades 2005)

- Same goals: 'Smooth within Similar Regions'
- KEY INSIGHT: Generalize, extend 'Similarity'
 - Bilateral:
Averages neighbors with similar intensities;
 - NL-Means:
Averages neighbors with similar neighborhoods!

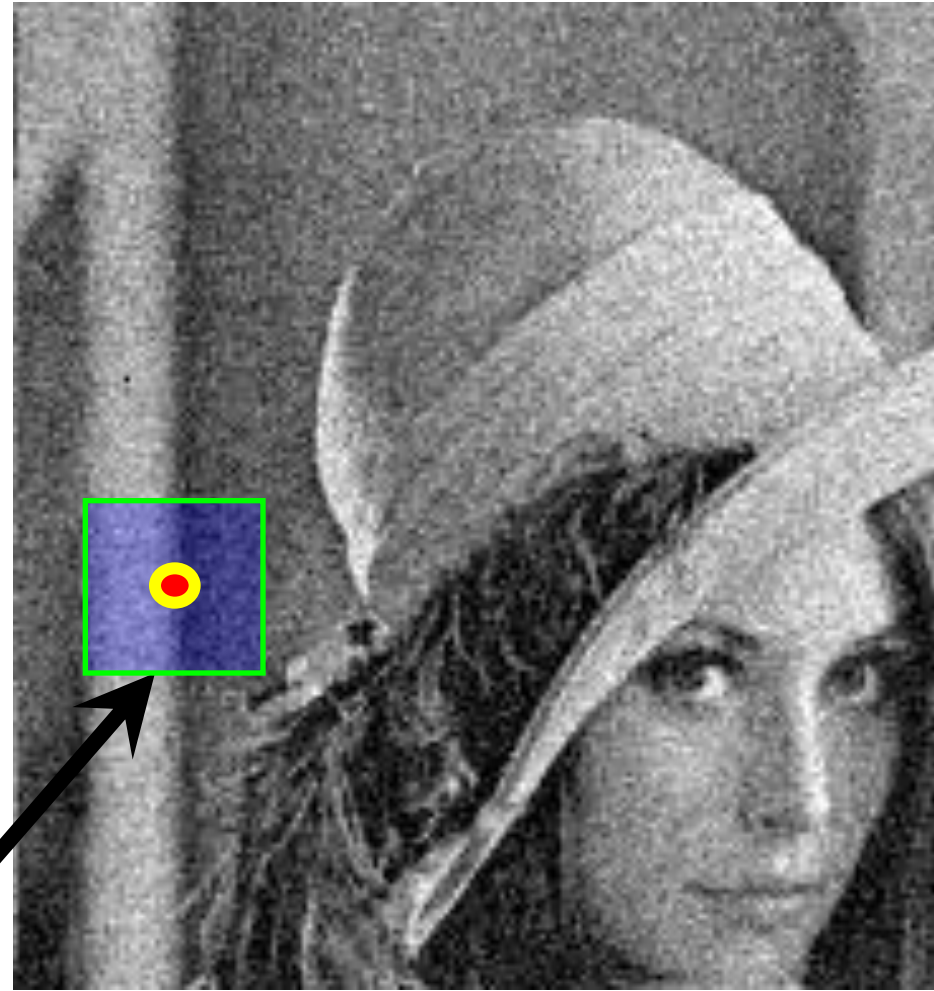
NL-Means Method

- For each and every pixel p :



NL-Means Method

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



NL-Means Method

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

- For each and every pixel p :

- Define a small, simple fixed size neighborhood;
- Define vector V_p : a list of neighboring pixel values.



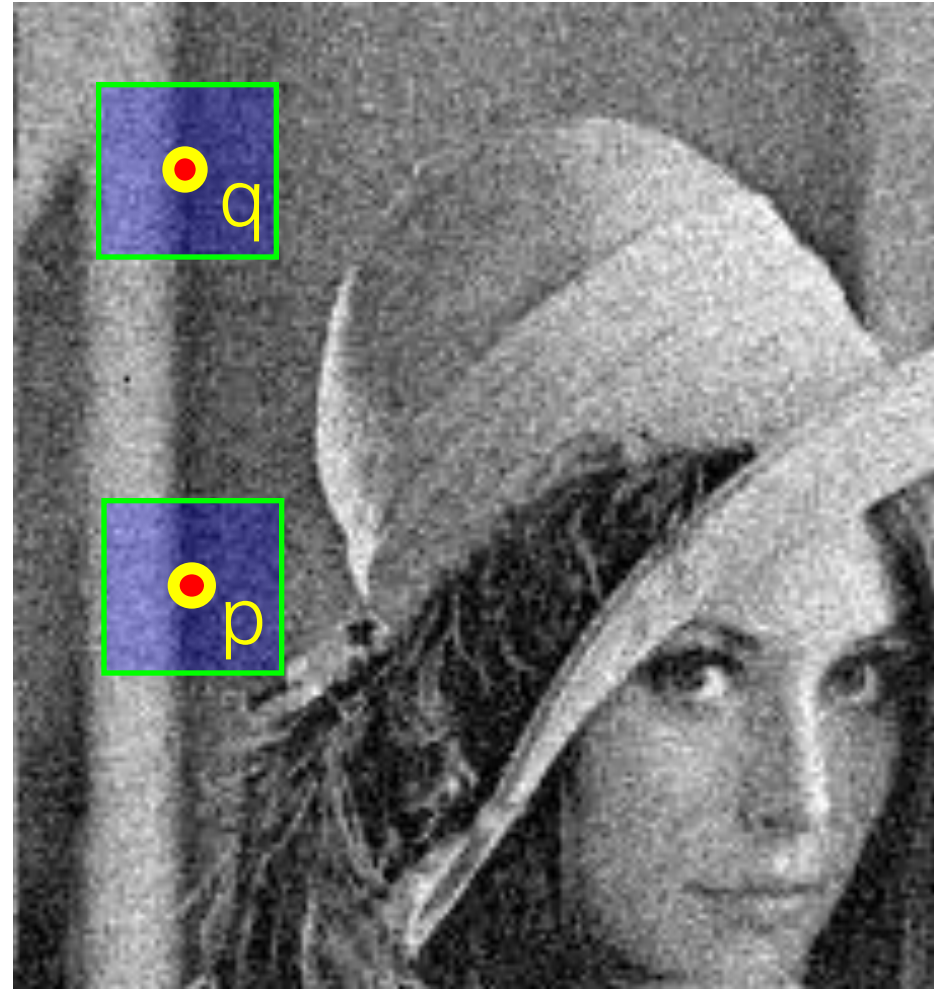
NL-Means Method

'Similar' pixels p, q

→ SMALL

vector distance;

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



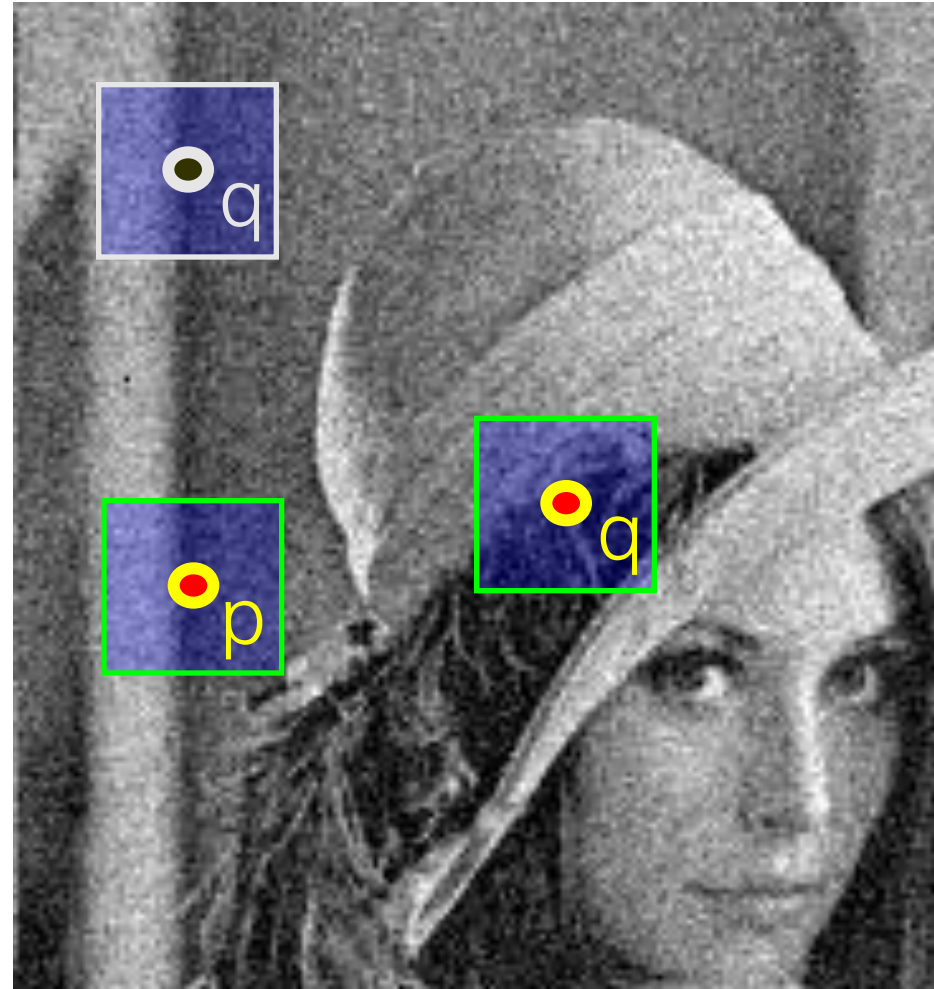
NL-Means Method

'Dissimilar' pixels p, q

→ LARGE

vector distance;

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



NL-Means Method

'Dissimilar' pixels p, q

→ LARGE
vector distance;

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

Filter with this!



NL-Means Method

p, q neighbors define
a vector distance;

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

Filter with this:

No spatial term!



$$NLMF[I]_p = \frac{1}{W_p} \sum_{q \in S} \cancel{G_{\sigma_s}(\|p - q\|)} G_{\sigma_r}(\| \vec{V}_p - \vec{V}_q \|^2) I_q$$

NL-Means Method

pixels p, q neighbors

Set a vector distance;

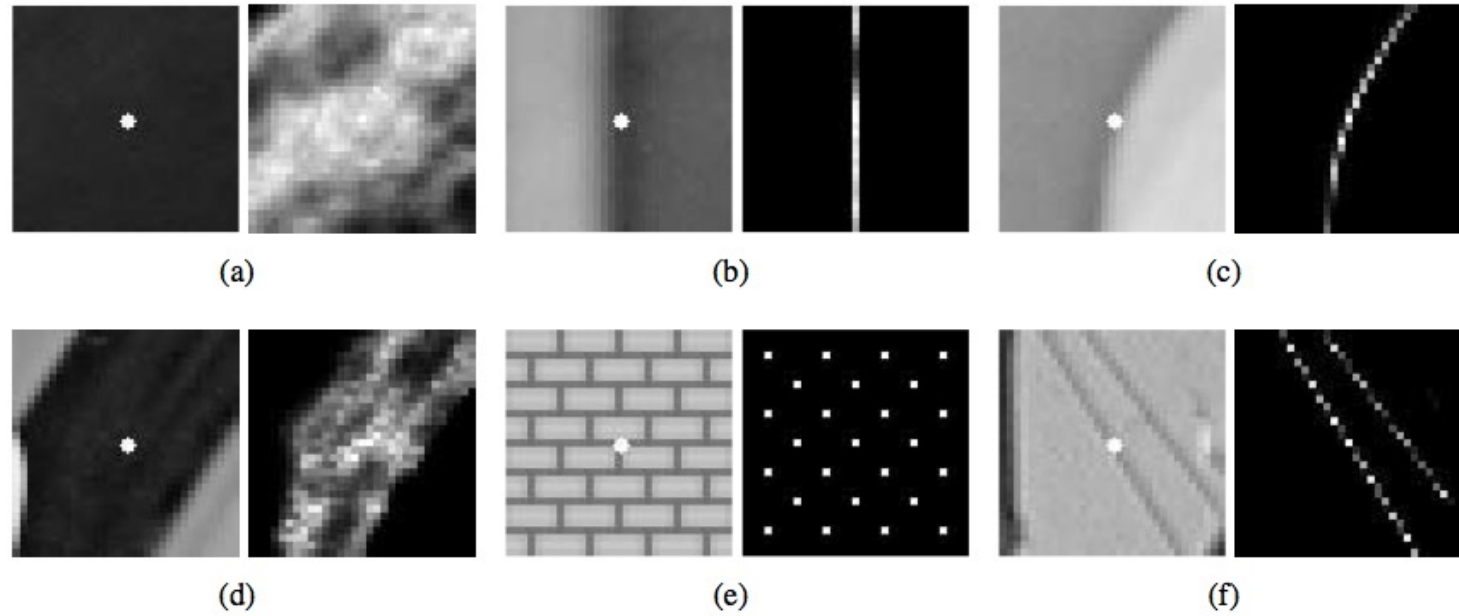
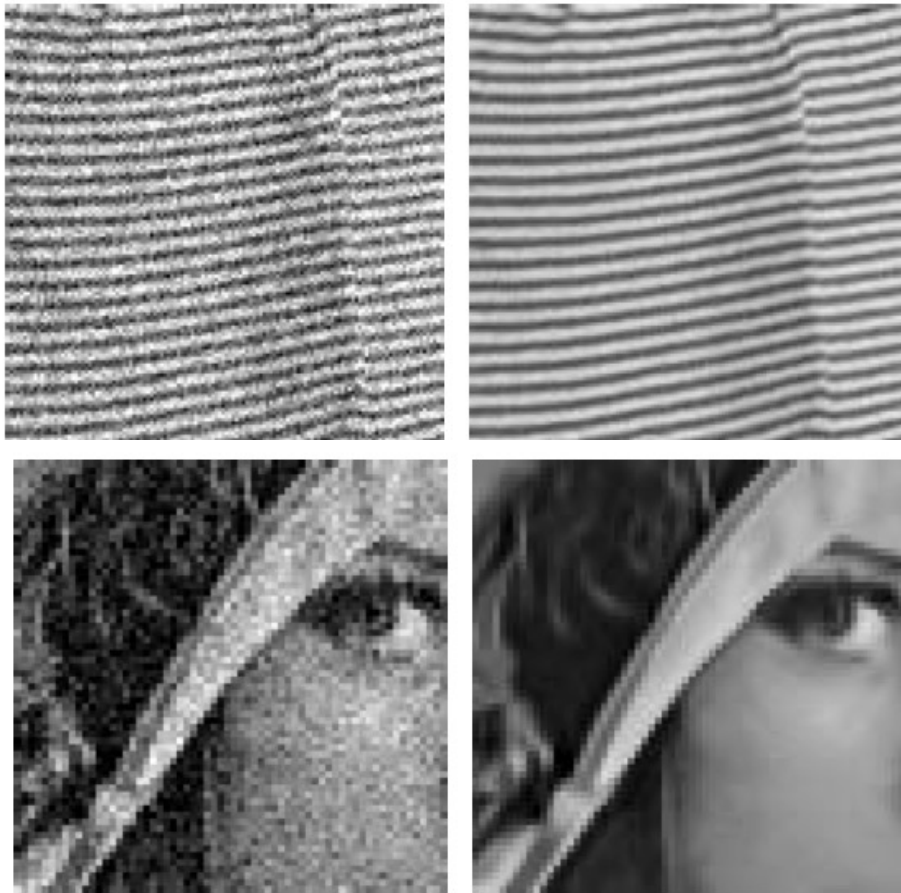
$$\|V_p - V_q\|^2$$

Vector Distance to p sets
weight for each pixel q



$$NLMF[I]_p = \frac{1}{W_p} \sum_{q \in S} G_{\sigma_r} \left(\| \vec{V}_p - \vec{V}_q \|^2 \right) I_q$$

NL-Means Method



NL-Means Method

- Noisy source image:



NL-Means Method

- Gaussian Filter

Low noise,
Low detail



NL-Means Method

- Anisotropic Diffusion

Note 'stairsteps':
~ piecewise constant



NL-Means Method

- Bilateral Filter

Better, but similar
'stairsteps':



NL-Means Method

- NL-Means:

Sharp,

Low noise,

Few artifacts.



NL-Means Method

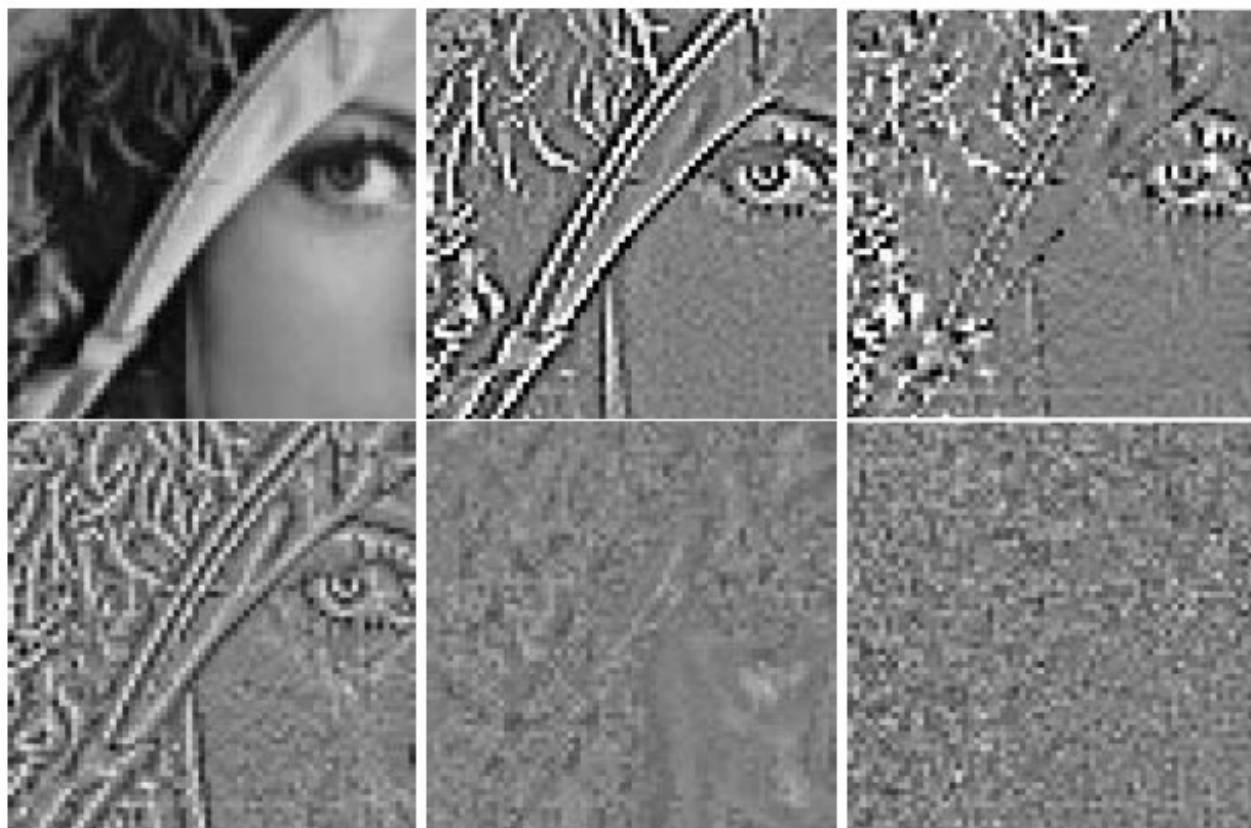


Figure 4. Method noise experience on a natural image. Displaying of the image difference $u - D_h(u)$. From left to right and from top to bottom: original image, Gauss filtering, anisotropic filtering, Total variation minimization, Neighborhood filtering and NL-means algorithm. The visual experiments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

NL-Means Method

original



noisy, standard deviation 15



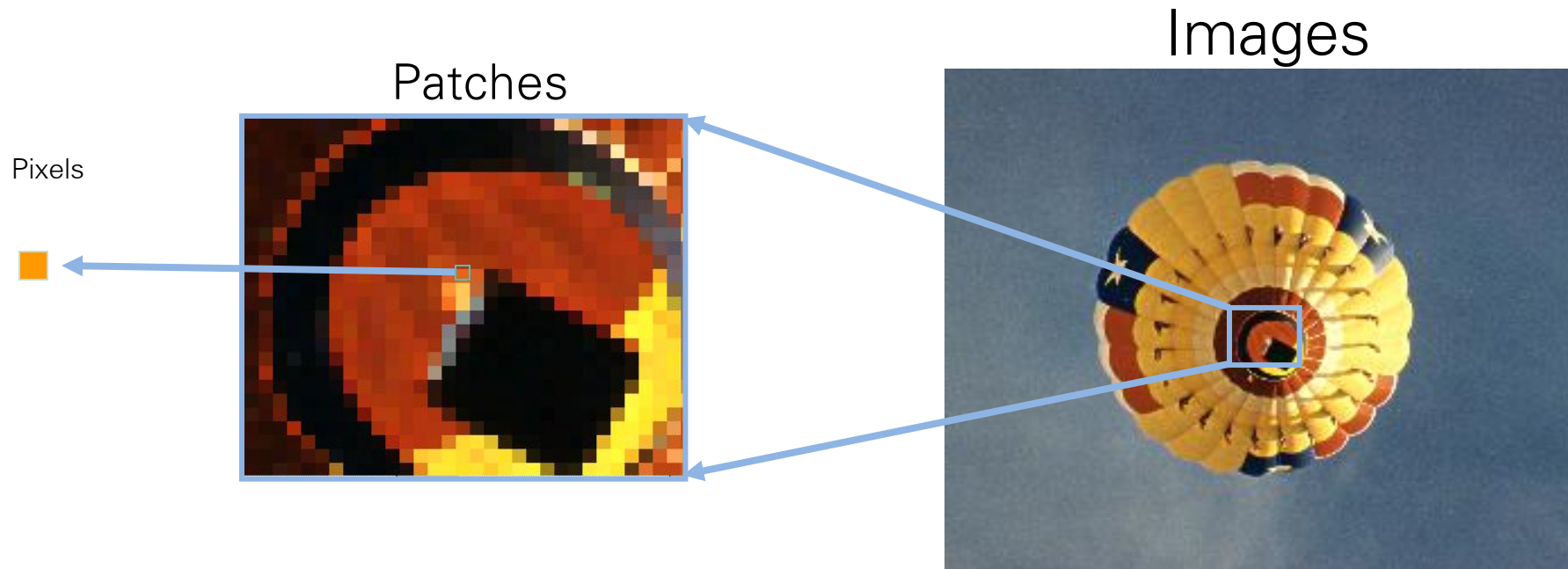
denoised



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

RegCov Smoothing

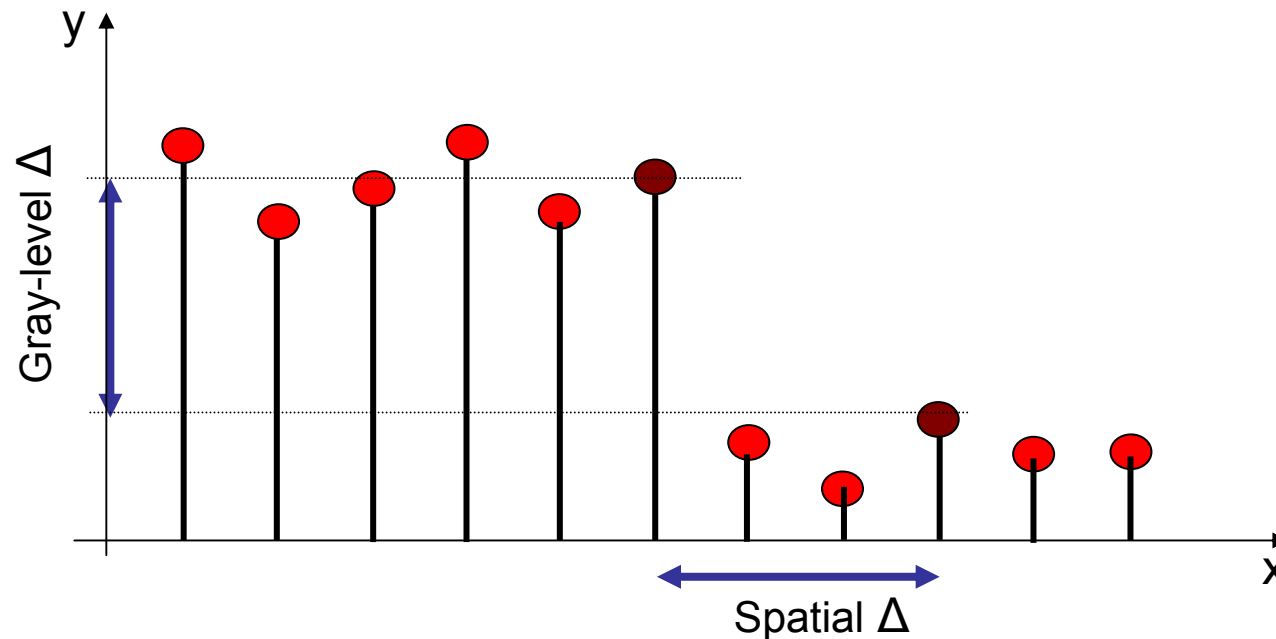
From pixels to patches and to images



Similarities can be defined at different scales..

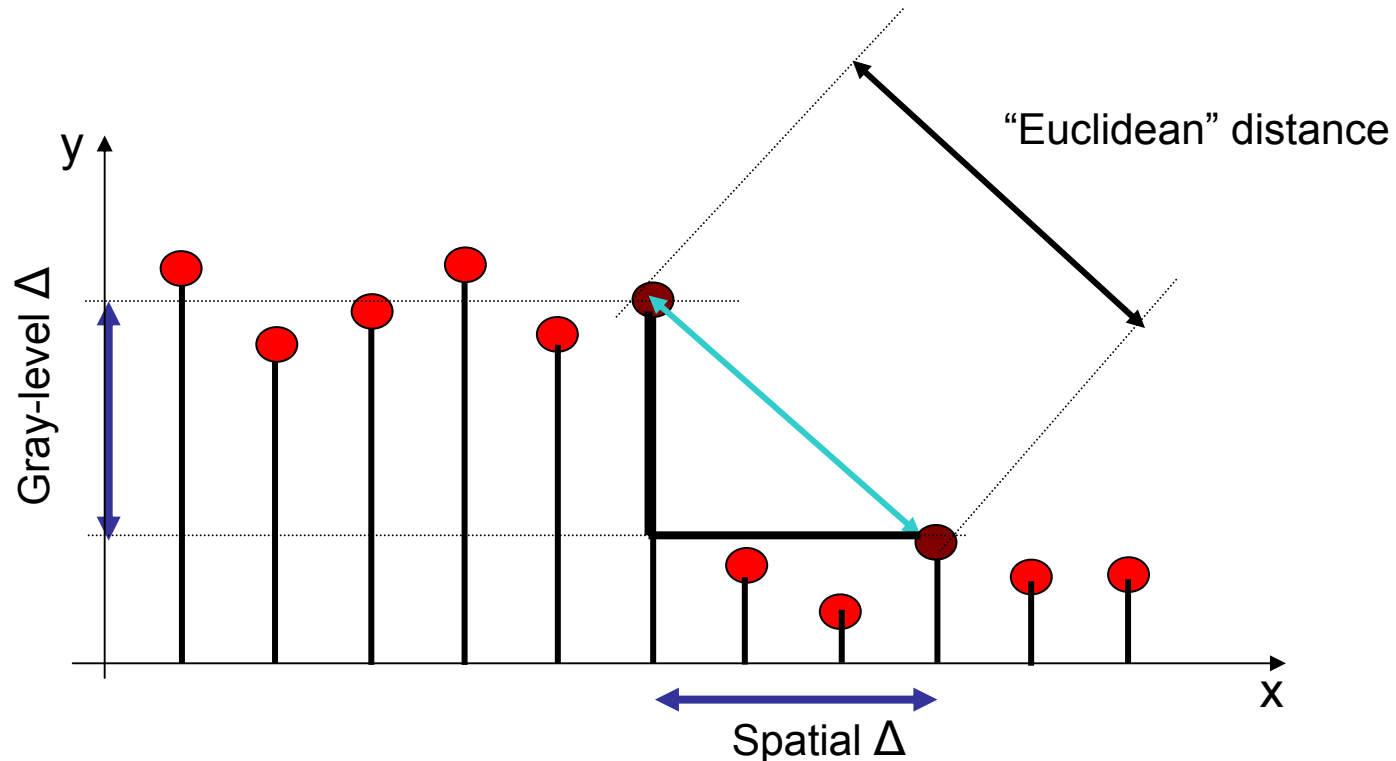
Pixelwise similarity metrics

- To measure the similarity of two pixels, we can consider
 - Spatial distance
 - Gray-level distance



Euclidean metrics

- Natural ways to incorporate the two Δ s:
 - Bilateral Kernel [Tomasi, Manduchi, '98] (pixelwise)
 - Non-Local Means Kernel [Buades, et al. '05] (patchwise)

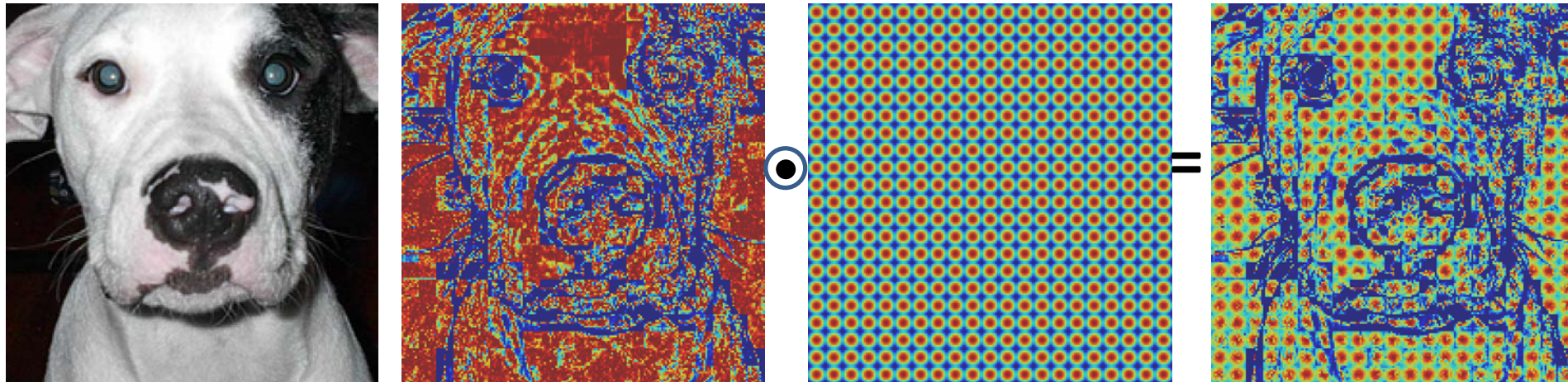


Bilateral Kernel (BL) [Tomasi et al. '98]

$$K(\mathbf{x}_l, \mathbf{x}, y_l, y) = \exp \left\{ - \frac{\|y_l - y\|^2}{h_r^2} - \frac{\|\mathbf{x}_l - \mathbf{x}\|^2}{h_d^2} \right\}$$

↓ ↓

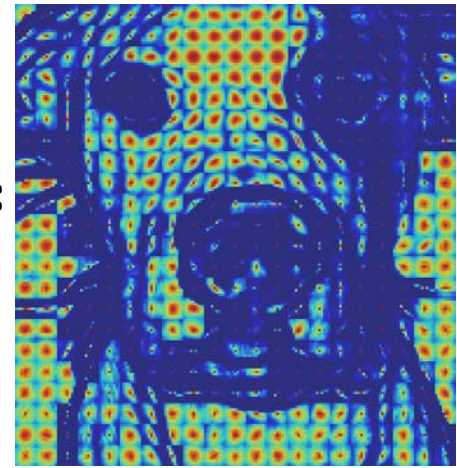
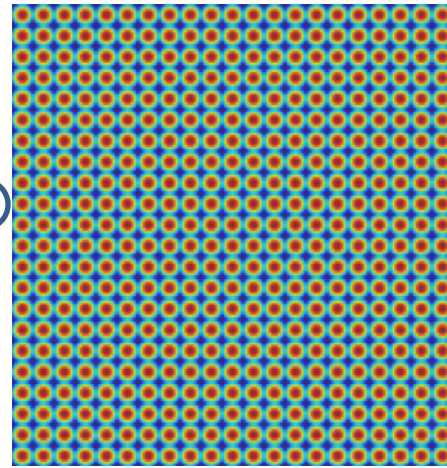
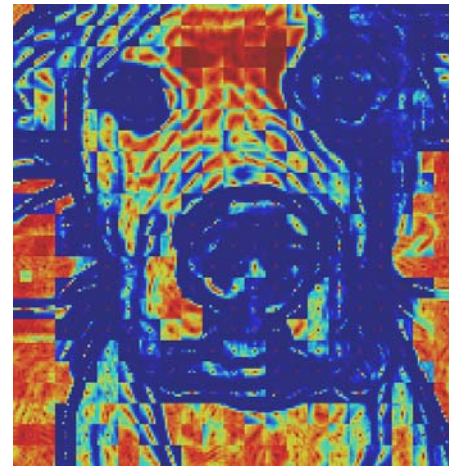
Pixel similarity **Spatial** similarity



Non-local Means (NLM) [Buades et al. '05]

$$K(\mathbf{x}_l, \mathbf{x}, \mathbf{y}_l, \mathbf{y}) = \exp \left\{ -\frac{\|\mathbf{y}_l - \mathbf{y}\|^2}{h_r^2} - \frac{\|\mathbf{x}_l - \mathbf{x}\|^2}{h_d^2} \right\}$$

Patches
↓
Patch similarity **Spatial** similarity



Smoothing effect

Structure-Texture Decomposition

- Decomposing an image into structure and texture components

Input Image



Structure-Texture Decomposition

- Decomposing an image into structure and texture components

Structure Component



Structure-Texture Decomposition

- Decomposing an image into structure and texture components

Texture Component



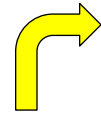
Structure-Texture Decomposition

- Decomposing an image into structure and texture components

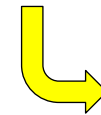
Input Image



Structure



Texture



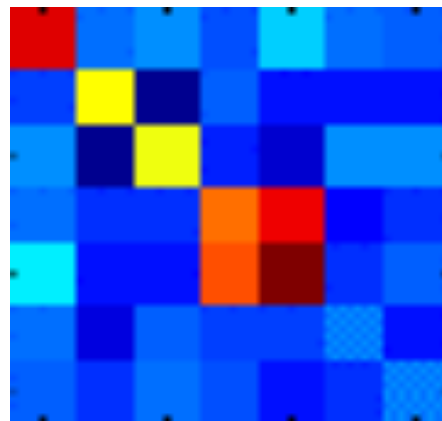
Structure-Texture Decomposition



$$F(x, y) = \phi(I, x, y)$$



$$F(x, y) = \left[I(x, y) \quad \left| \frac{\partial I}{\partial x} \right| \quad \left| \frac{\partial I}{\partial y} \right| \quad \left| \frac{\partial^2 I}{\partial x^2} \right| \quad \left| \frac{\partial^2 I}{\partial y^2} \right| \quad x \quad y \right]^T$$



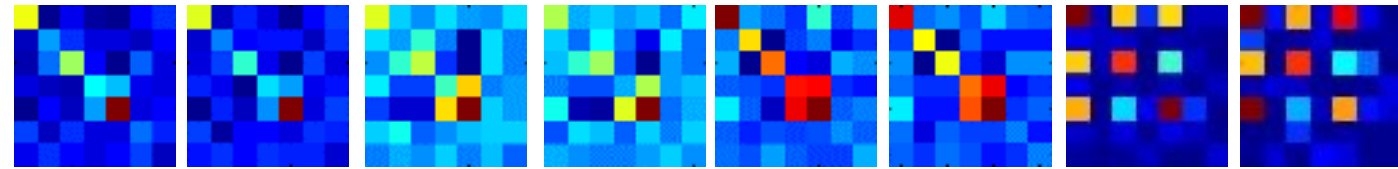
$$\mathbf{C}_R = \frac{1}{n-1} \sum_{i=0}^n (\mathbf{z}_k - \mu)(\mathbf{z}_k - \mu)^T$$

Tuzel et al., ECCV 2006

Structure-Texture Decomposition



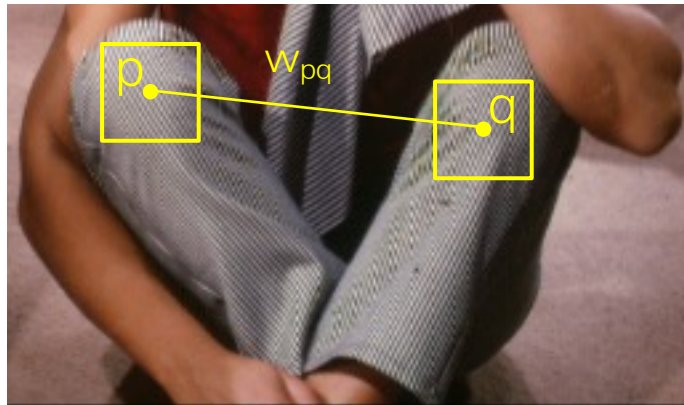
- Region covariances capture local structure and texture information.
- Similar regions have similar statistics.



RegCov Smoothing - Formulation

$$I = S + T$$

$$S(\mathbf{p}) = \frac{1}{Z_{\mathbf{p}}} \sum_{\mathbf{q} \in N(\mathbf{p}, r)} w_{\mathbf{p}\mathbf{q}} I(\mathbf{q})$$



- Structure-texture decomposition via smoothing
- Smoothing as weighted averaging
- Different kernels ($w_{\mathbf{p}\mathbf{q}}$) result in different types of filters.
- Three novel patch-based kernels for structure texture decomposition.

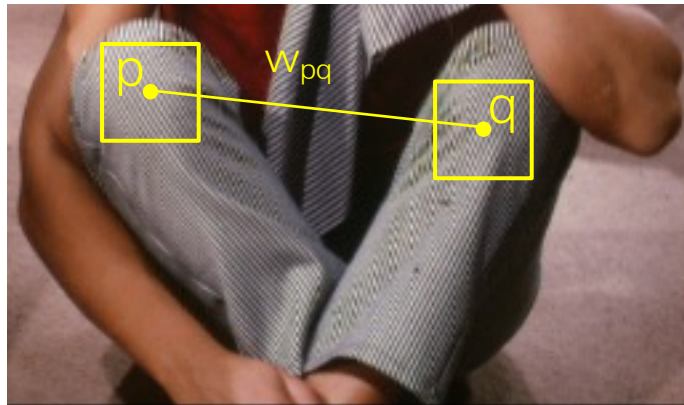
- L. Karacan, A. Erdem, E. Erdem, "Structure Preserving Image Smoothing via Region Covariances", ACM TOG 2013 (SIGGRAPH Asia 2013)

RegCov Smoothing – Model 1

- Depends on sigma-points representation of covariance matrices (Hong et al., CVPR'09)

$$\mathbf{C} = \mathbf{L}\mathbf{L}^T \quad \text{Cholesky Decomposition}$$

$$\mathcal{S} = \{\mathbf{s}_i\} \quad \text{Sigma Points} \quad \mathbf{s}_i = \begin{cases} \alpha\sqrt{d}\mathbf{L}_i & \text{if } 1 \leq i \leq d \\ -\alpha\sqrt{d}\mathbf{L}_i & \text{if } d+1 \leq i \leq 2d \end{cases}$$



Final representation

$$\Psi(\mathbf{C}) = (\mu, \mathbf{s}_1, \dots, \mathbf{s}_d, \mathbf{s}_{d+1}, \dots, \mathbf{s}_{2d})^T$$

Resulting kernel function

$$w_{\mathbf{p}\mathbf{q}} \propto \exp\left(-\frac{\|\Psi(\mathbf{C}_{\mathbf{p}}) - \Psi(\mathbf{C}_{\mathbf{q}})\|^2}{2\sigma^2}\right)$$

RegCov Smoothing – Model 2

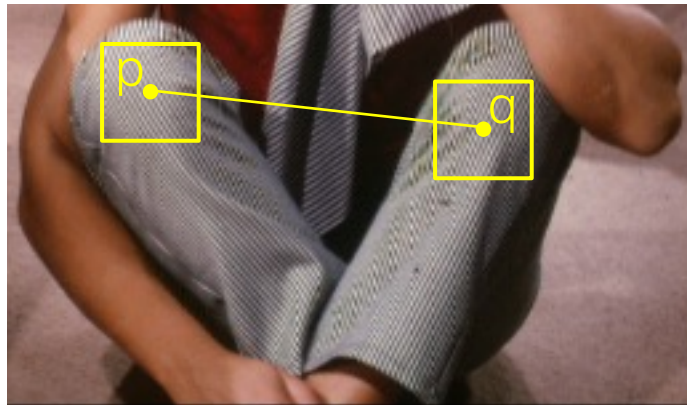
- An alternative way is to use statistical similarity measures.
- A Mahalanobis-like distance measure to compare to image patches.

$$d(\mathbf{p}, \mathbf{q}) = \sqrt{(\mu_{\mathbf{p}} - \mu_{\mathbf{q}}) \mathbf{C}^{-1} (\mu_{\mathbf{p}} - \mu_{\mathbf{q}})^T}$$

$$\mathbf{C} = \mathbf{C}_{\mathbf{p}} + \mathbf{C}_{\mathbf{q}}$$

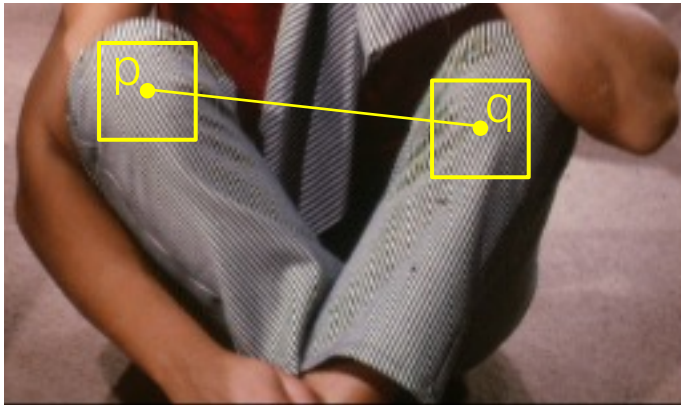
Resulting kernel

$$w_{\mathbf{p}\mathbf{q}} \propto \exp\left(-\frac{d(\mathbf{p}, \mathbf{q})^2}{2\sigma^2}\right)$$



RegCov Smoothing – Model 3

- We use Kullback-Leibler(KL)-Divergence measure from probability theory.
- A KL-Divergence form is used to calculate statistical distance between two multivariate normal distribution



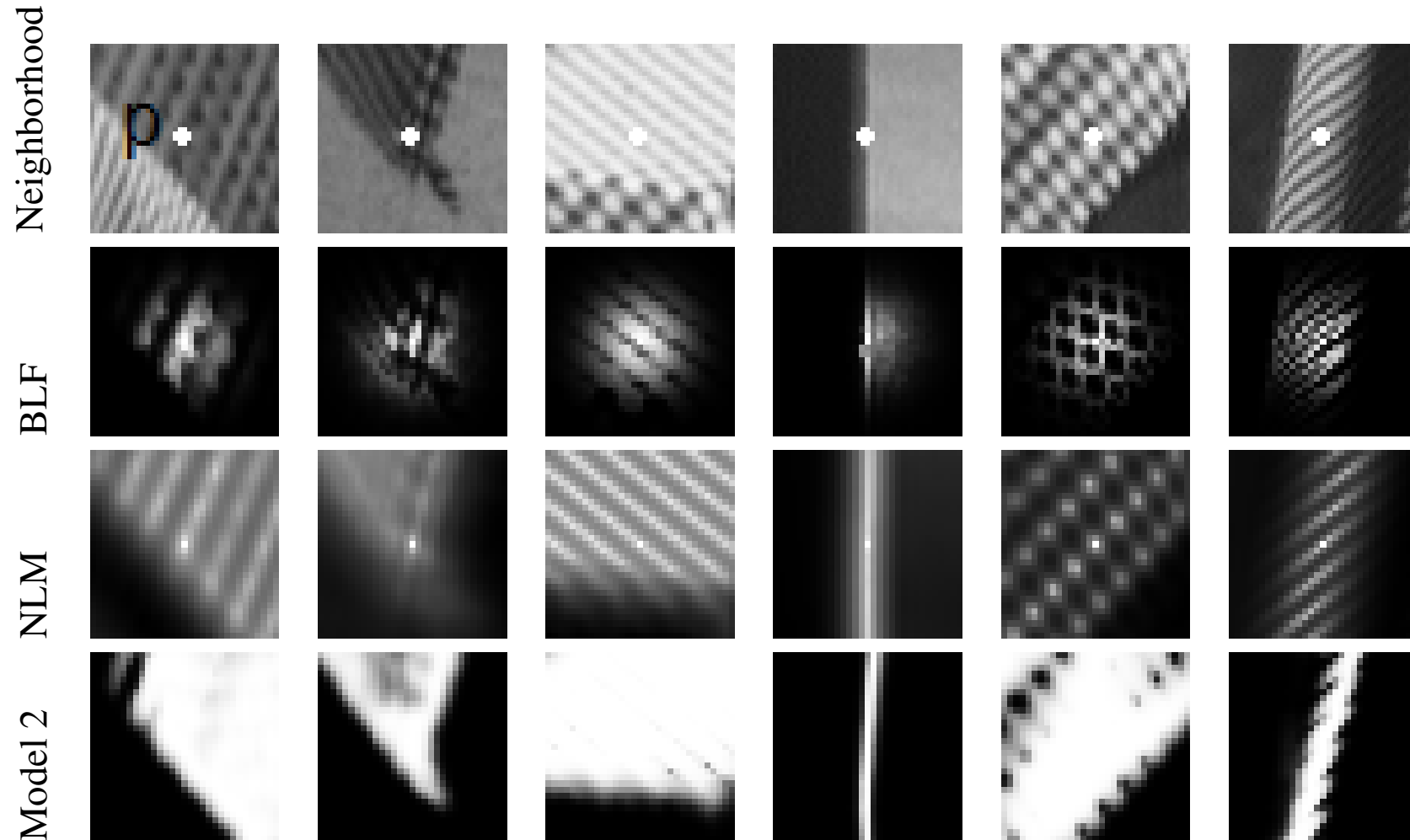
$$d_{KL}(\mathbf{p}, \mathbf{q}) = \frac{1}{2} \left(\text{tr}(\mathbf{C}_{\mathbf{q}}^{-1} \mathbf{C}_{\mathbf{p}}) + (\mu_{\mathbf{p}} - \mu_{\mathbf{q}})^T \mathbf{C}_{\mathbf{q}}^{-1} (\mu_{\mathbf{p}} - \mu_{\mathbf{q}}) - k - \ln \left(\frac{\det \mathbf{C}_{\mathbf{p}}}{\det \mathbf{C}_{\mathbf{q}}} \right) \right)$$

Resulting kernel

$$w_{pq} \propto \frac{d_{KL}(\mathbf{p}, \mathbf{q})}{2\sigma^2}$$

resulted from a discussion with Rahul Narain (Berkeley University)

RegCov Smoothing – Smoothing Kernels



Results



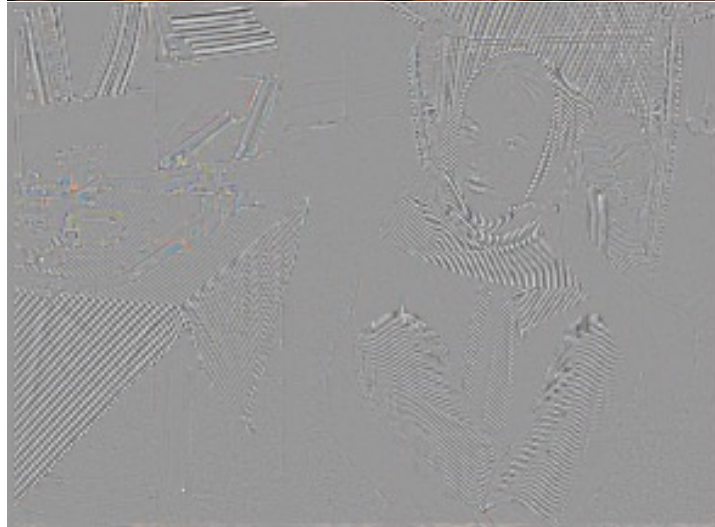
Input

Results

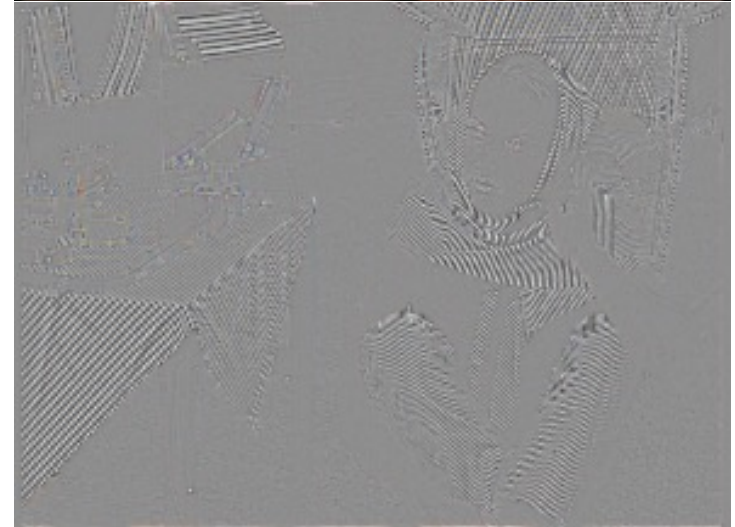
Model1



Model2

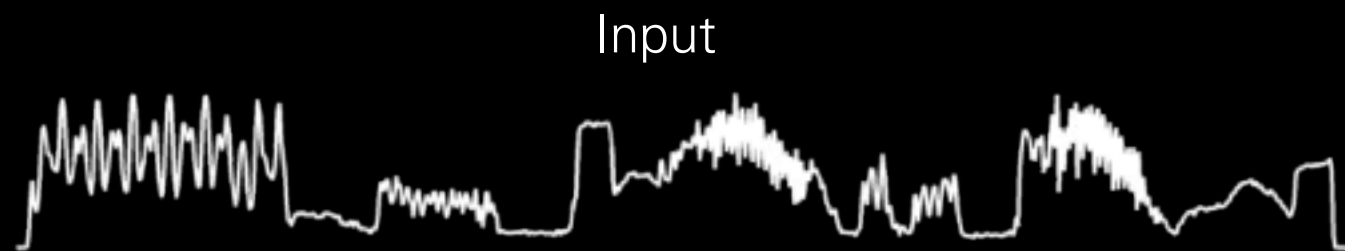


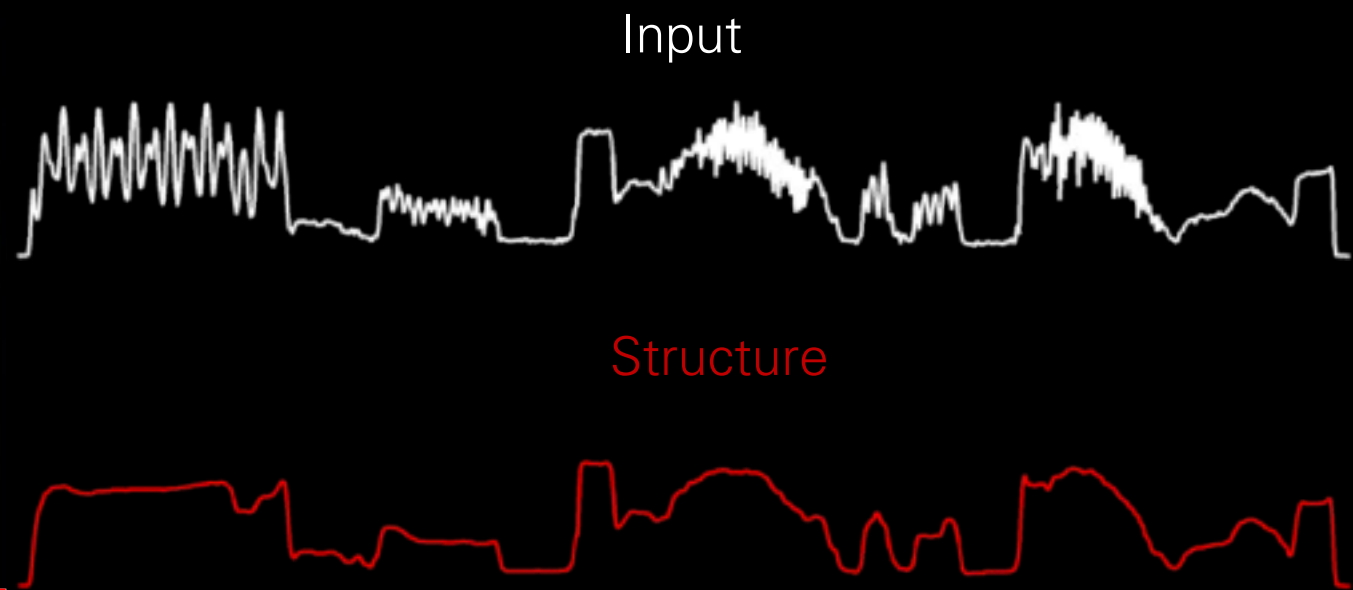
Model3



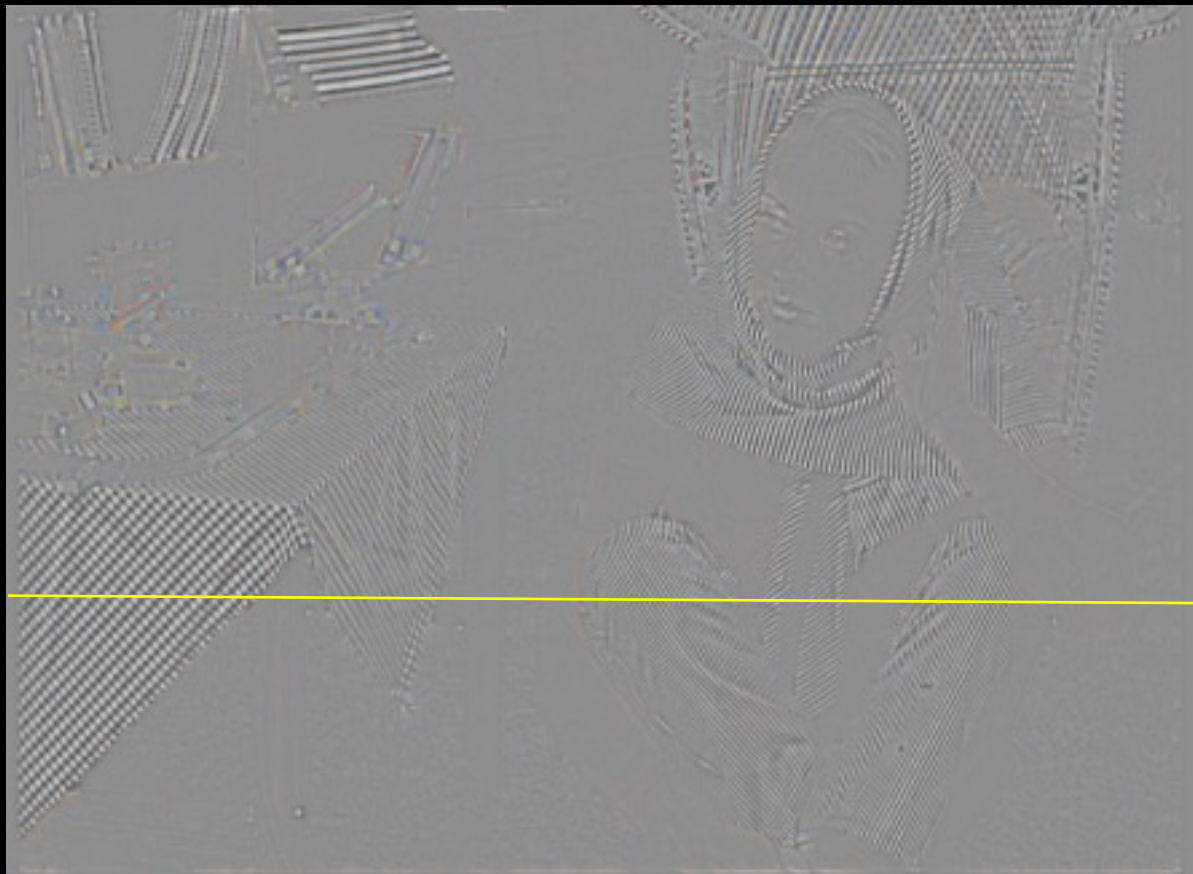


Input

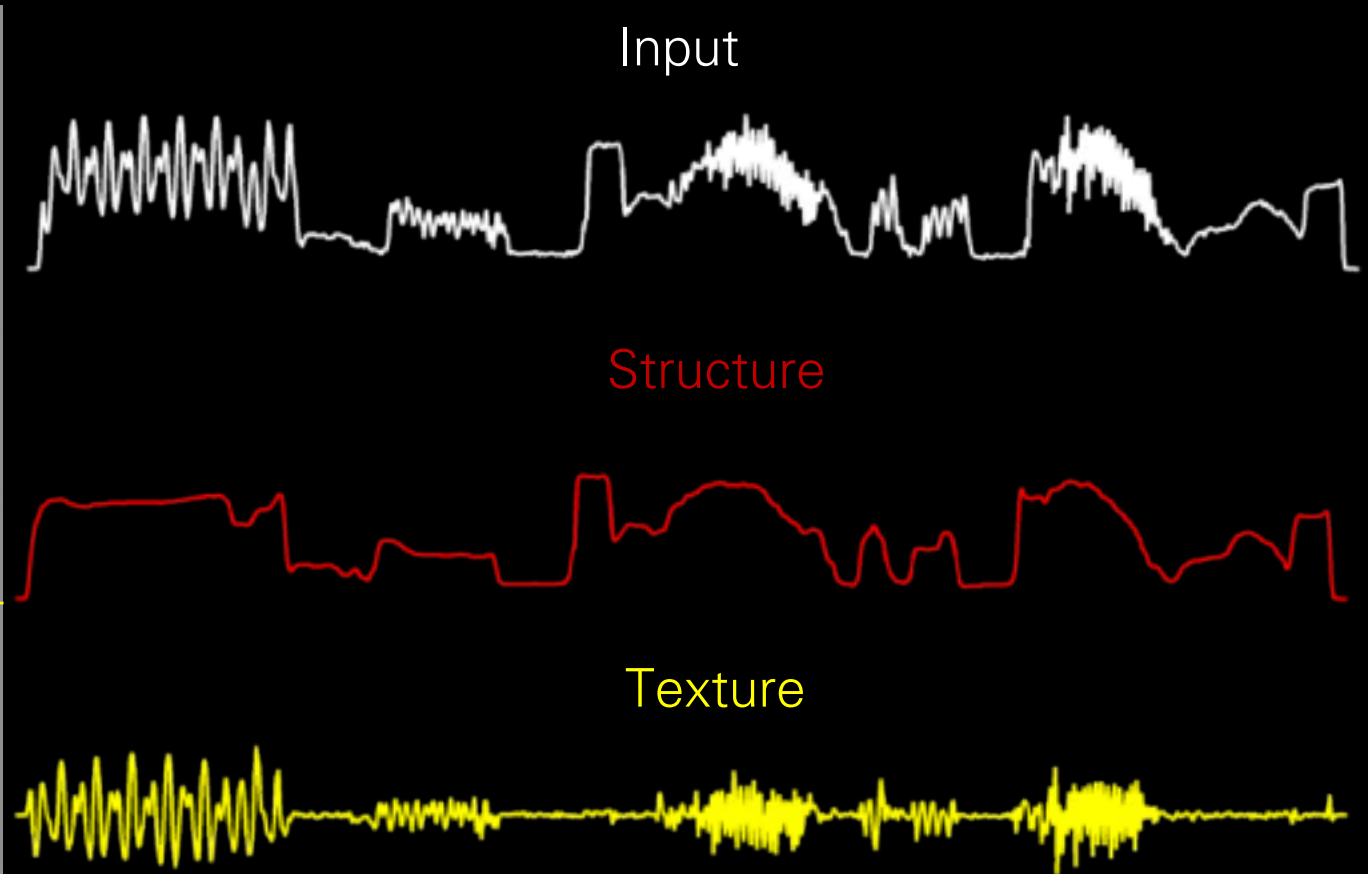




Model2 Structure



Model2 Texture

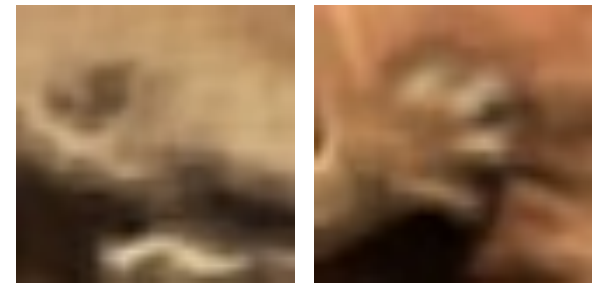
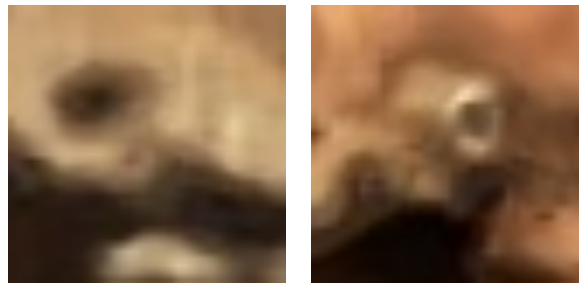
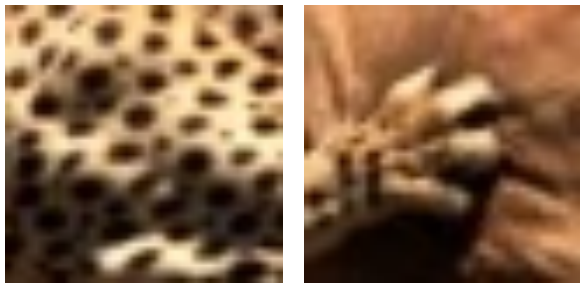
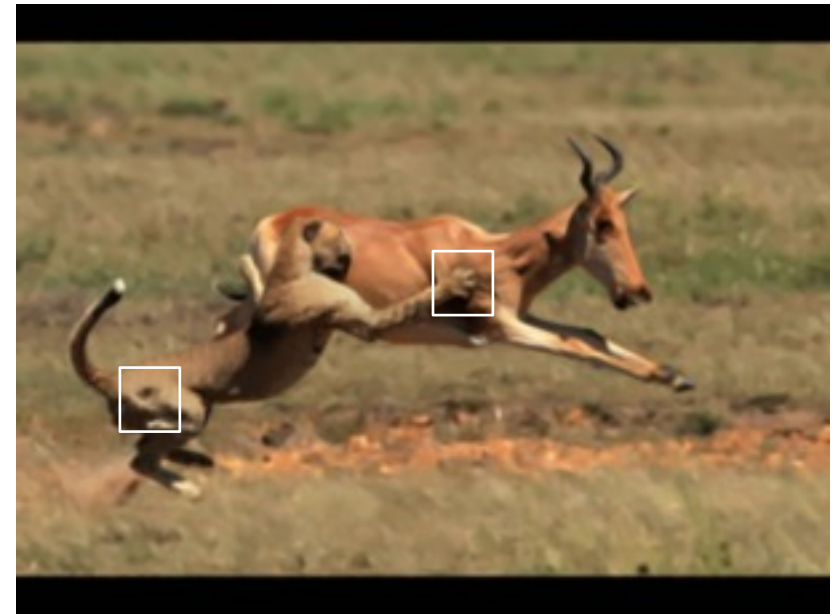
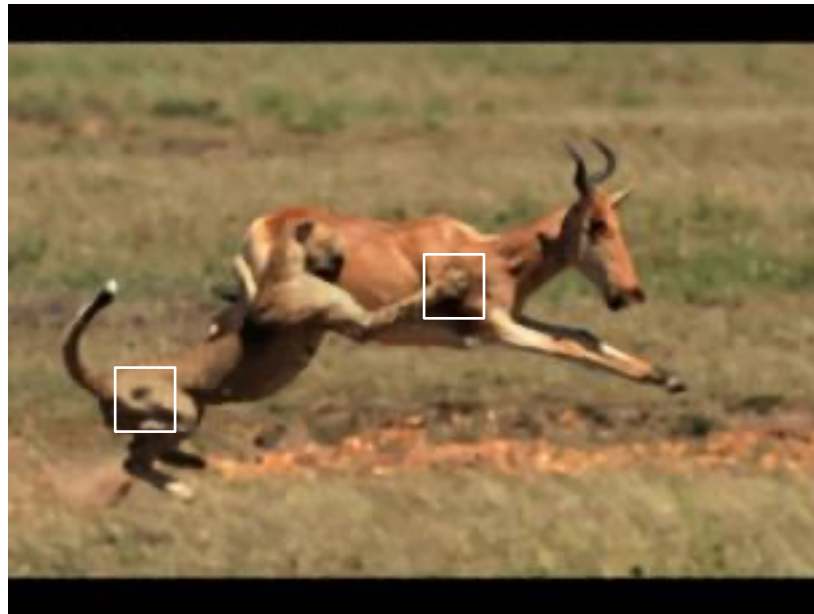
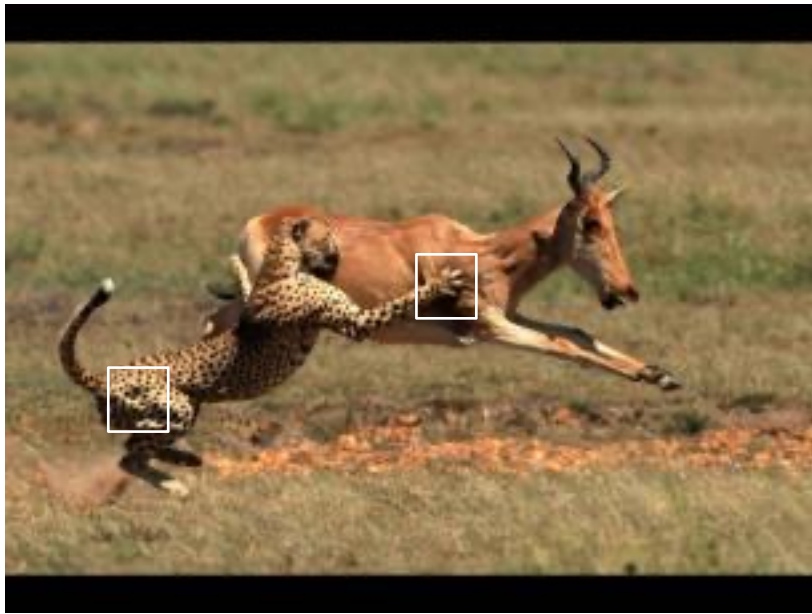


Results

Input

Model2

Model3



Experimental evaluation



Input

Experimental evaluation



TV

Rudin et al. 1992

Experimental evaluation



Bilateral
Filter

Experimental evaluation



Envelope Extraction

Subr et al. 2009

Experimental evaluation



RTV

Xu et al. 2012

Experimental evaluation



Model 1

Experimental evaluation



Model 2

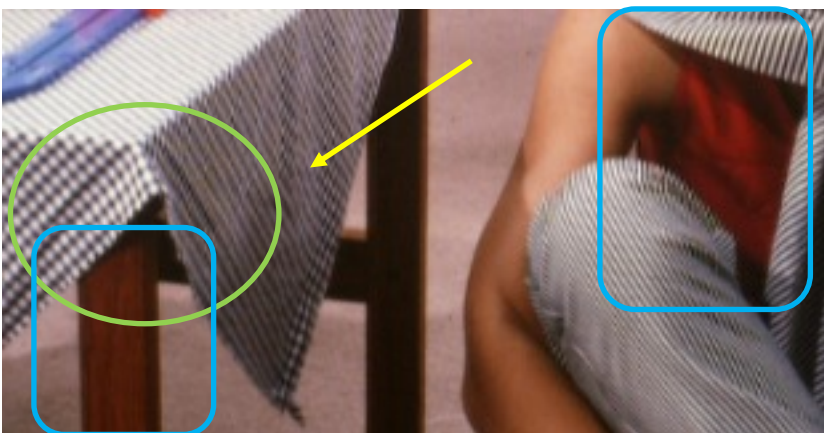
Experimental evaluation



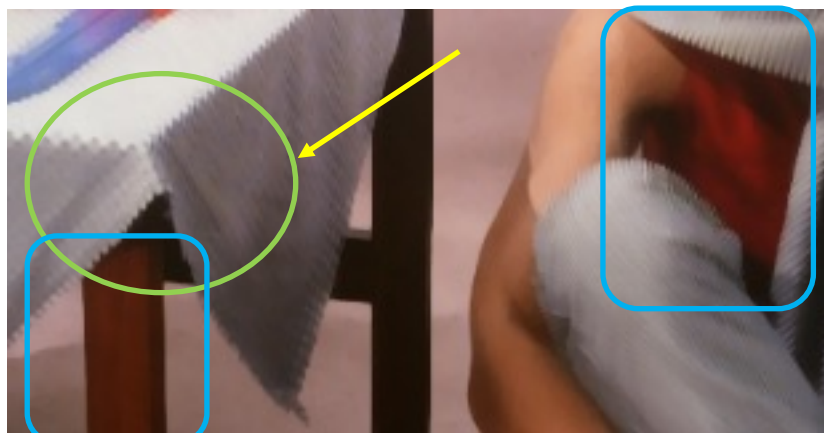
Model 3

Experimental evaluation

Input



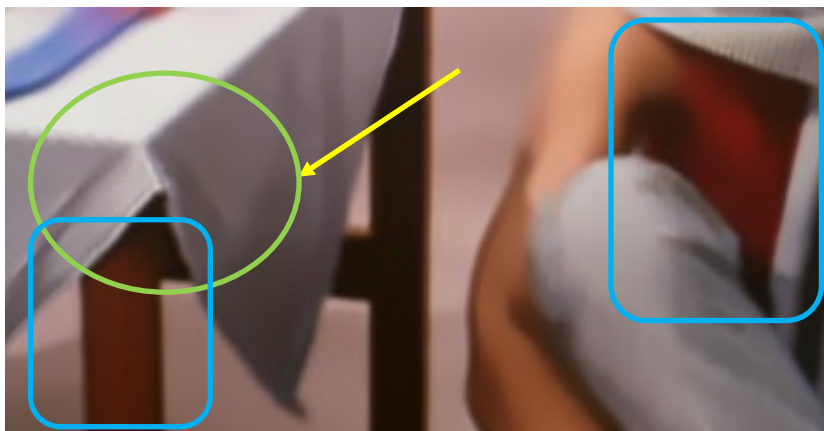
Local Exrema



RTV



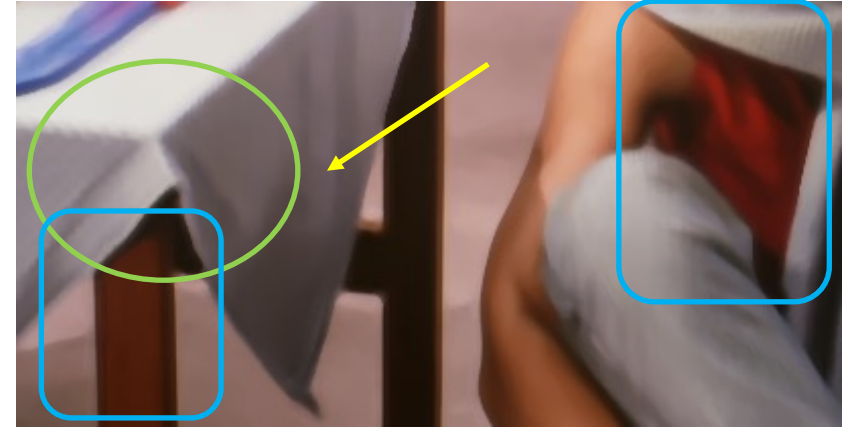
Model1



Model2



Model3

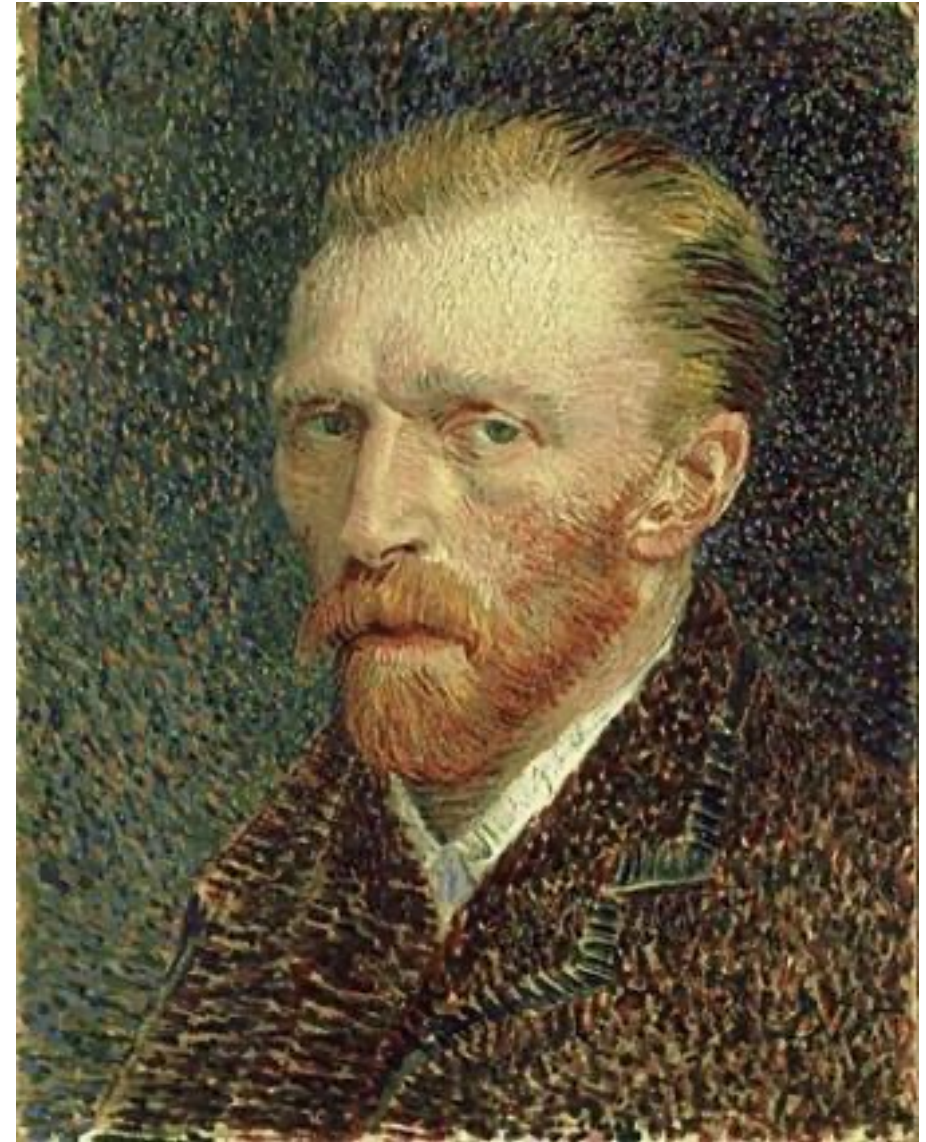


Shading preserved

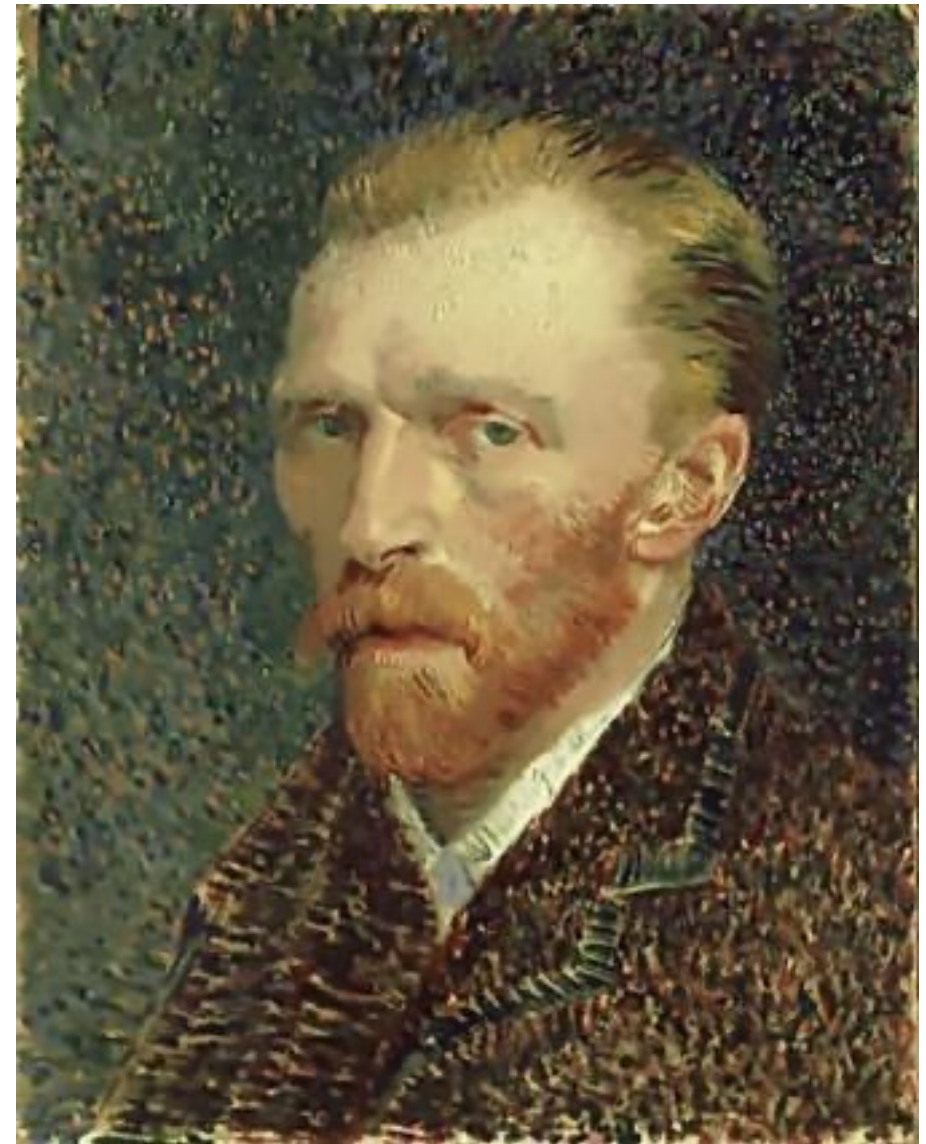
Structure preserved

No unintuitive edge

Multiscale decomposition



Multiscale decomposition



$S_1(k = 5)$

Multiscale decomposition



$S_2(k = 7)$

Multiscale decomposition



$S_3(k=9)$



Challenging cases

Input



Model2

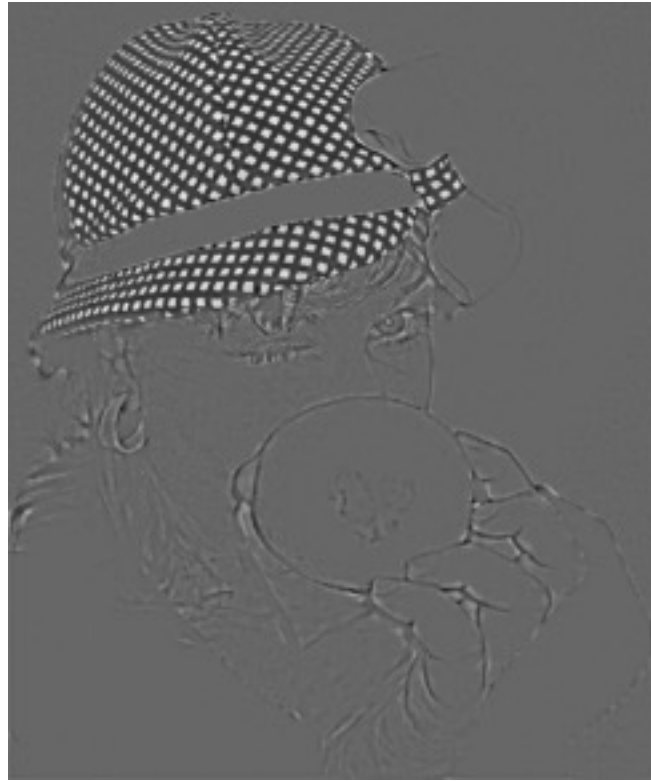


Challenging cases

Input



Model2 Texture



Model2+Model1



Edge detection



Edge detection



Edge detection

Canny edges of original image



Canny edges of smoothed image

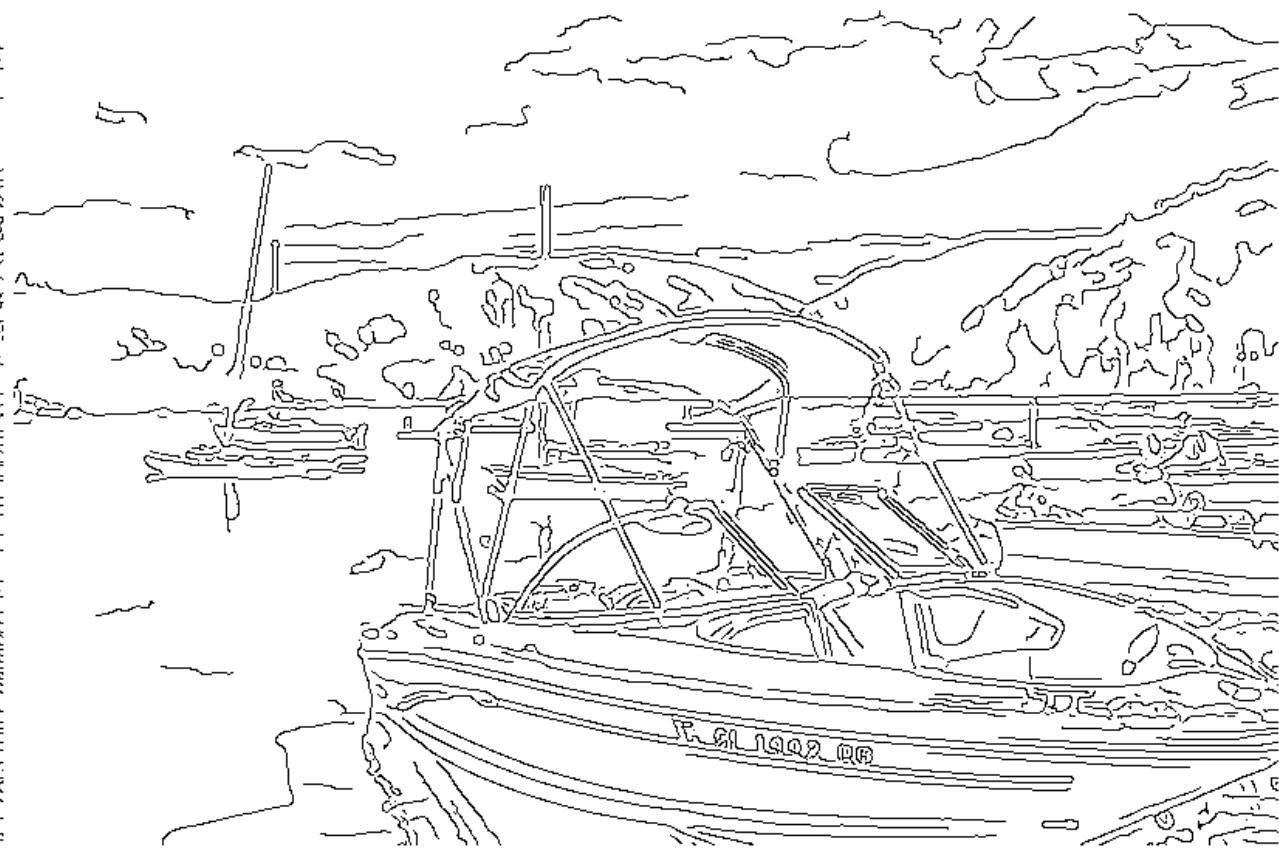


Image abstraction



Image abstraction



Detail boosting



Image composition



Inverse Halftoning



Input
halftone image

Inverse Halftoning



Smoothed image
(Model 2)

Inverse Halftoning



Smoothed image
(Model 2 + Shock filter)

Inverse Halftoning



Model2+Shock Filter



Input halftone image



Kopf and Lischinski 2012

Image Retargeting

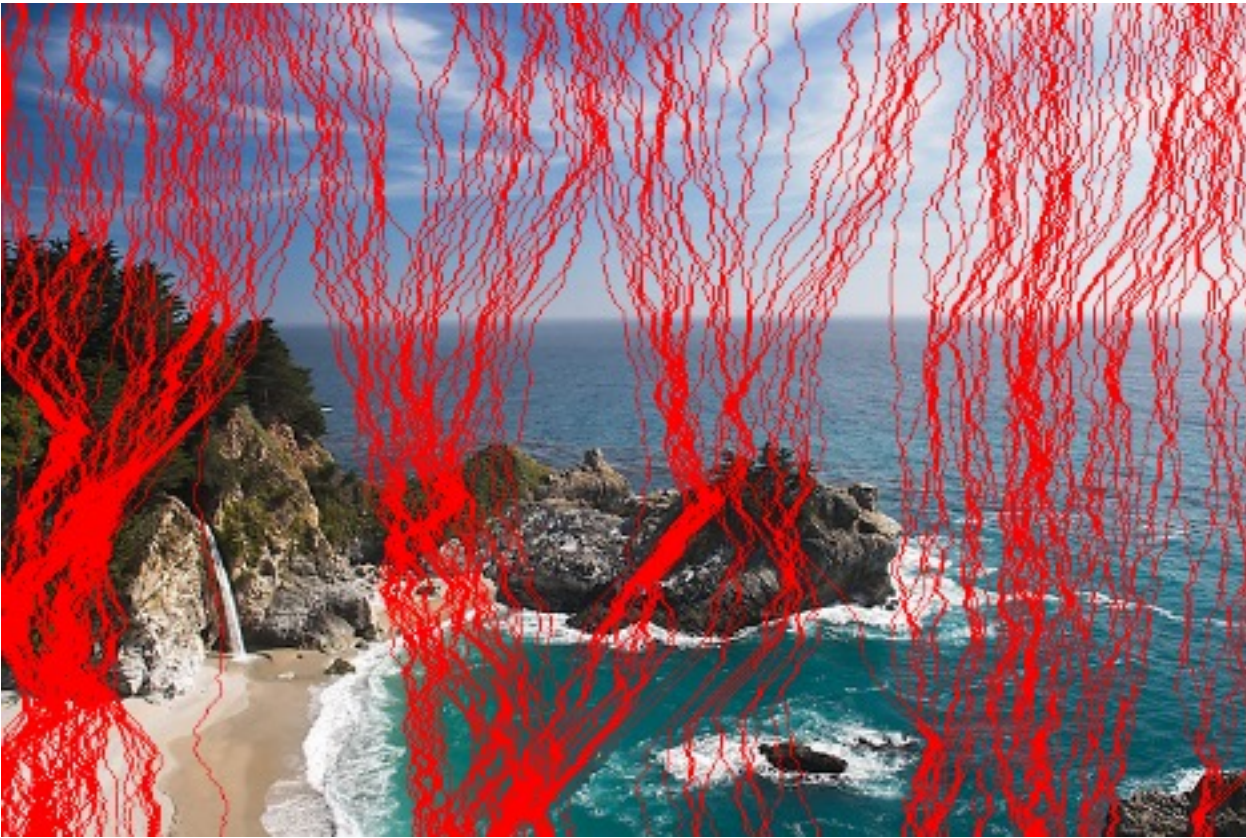


Input image



Smoothed image

Image Retargeting



Input image
Extracted Seams



Smoothed image
Extracted Seams

Image Retargeting



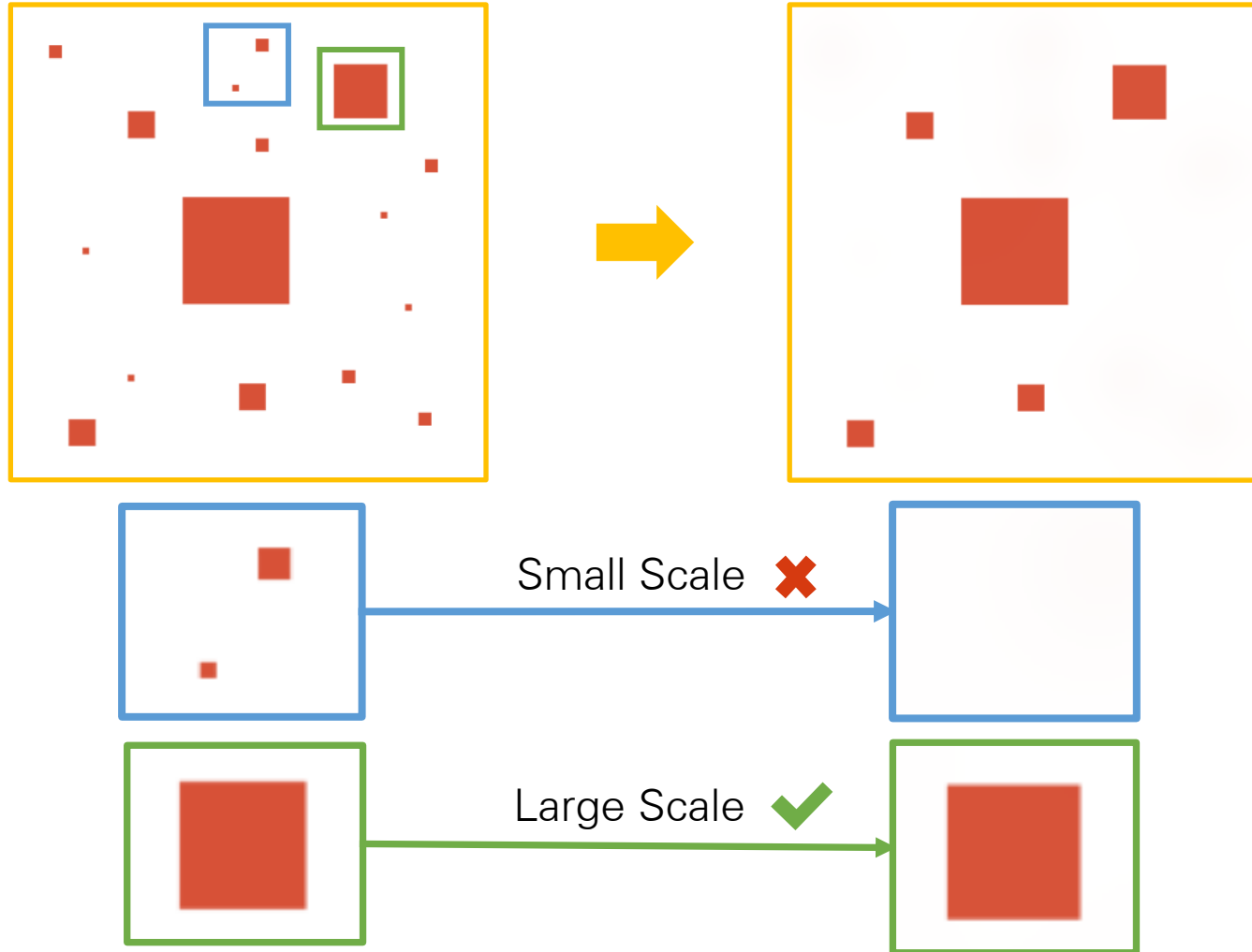
Input image
Retargeting result



Smoothed image
Retargeting result

Rolling Guidance Filter

Scale-Aware Filtering



Notion of Scale in Filtering

input image

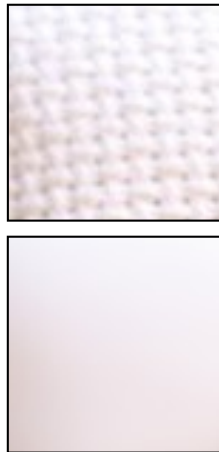


$s = 0$

texture disappear



$s = 4$



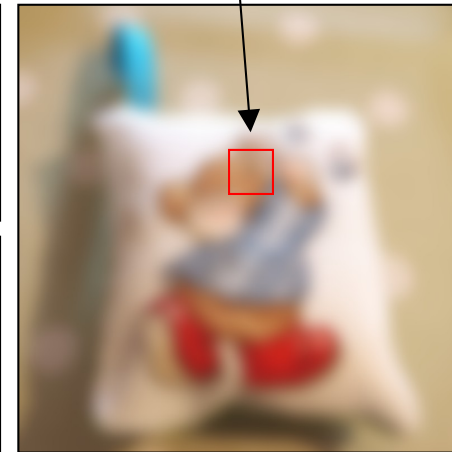
white dots disappear



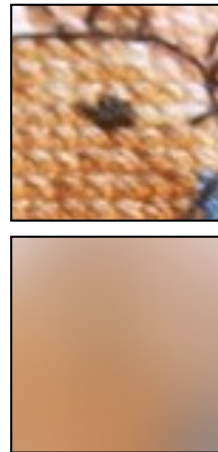
$s = 8$



the eye disappears



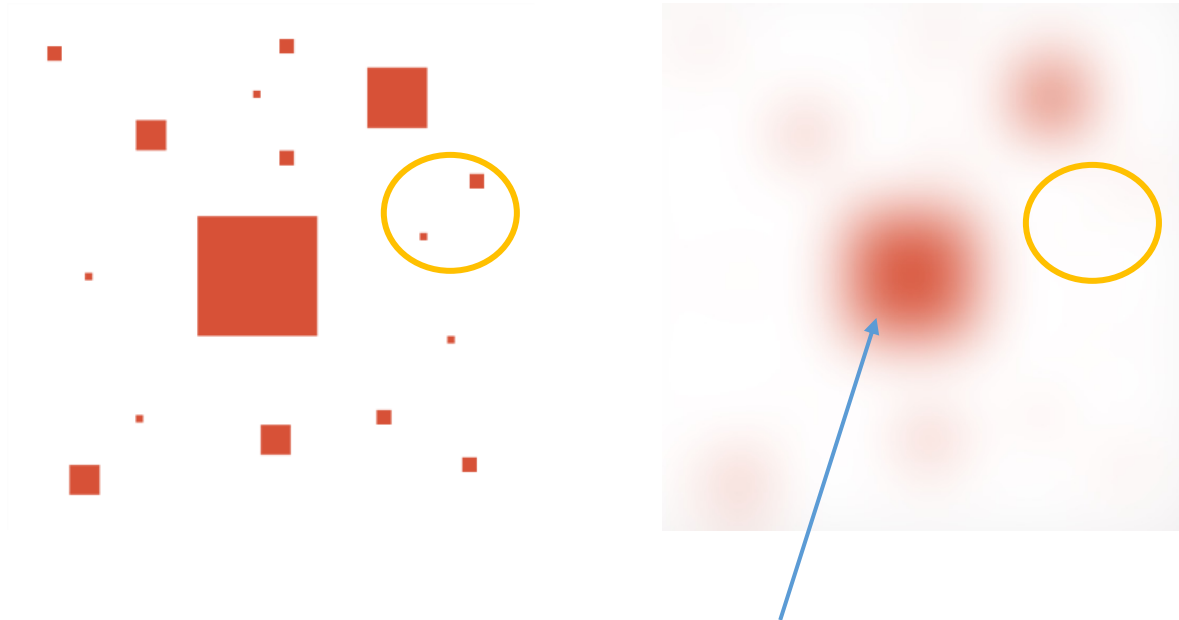
$s = 14$



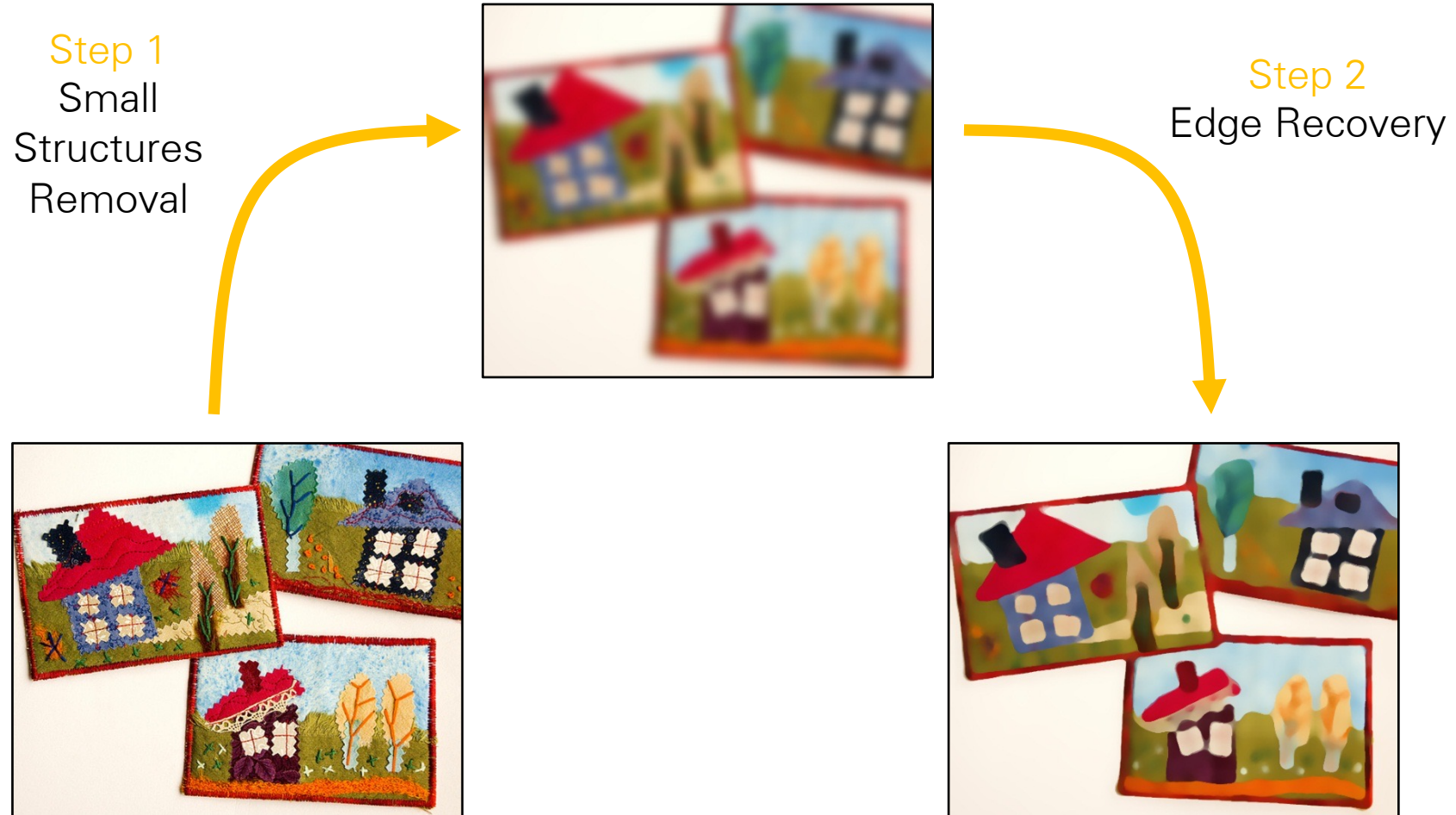
As the Gaussian kernel gets larger, more and more structures disappear.

Main Idea

- Scale Space Theory [Lindeberg, 1994]:
 - An object of size t , will be largely smoothed away with Gaussian filter of variance t^2 .



RGF: A scale-aware Filter



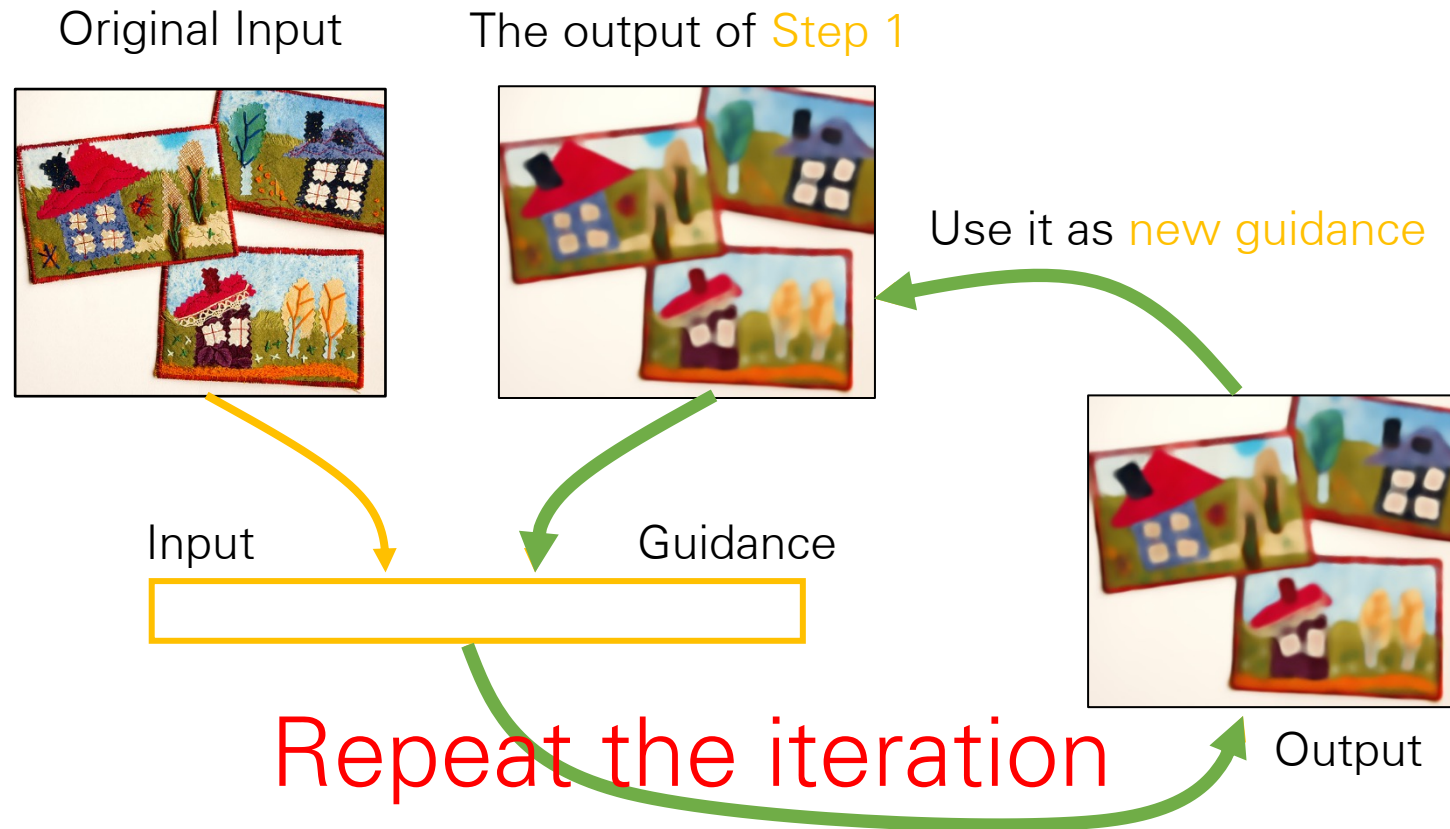
Step 1: Small Structures Removal

Gaussian Filter

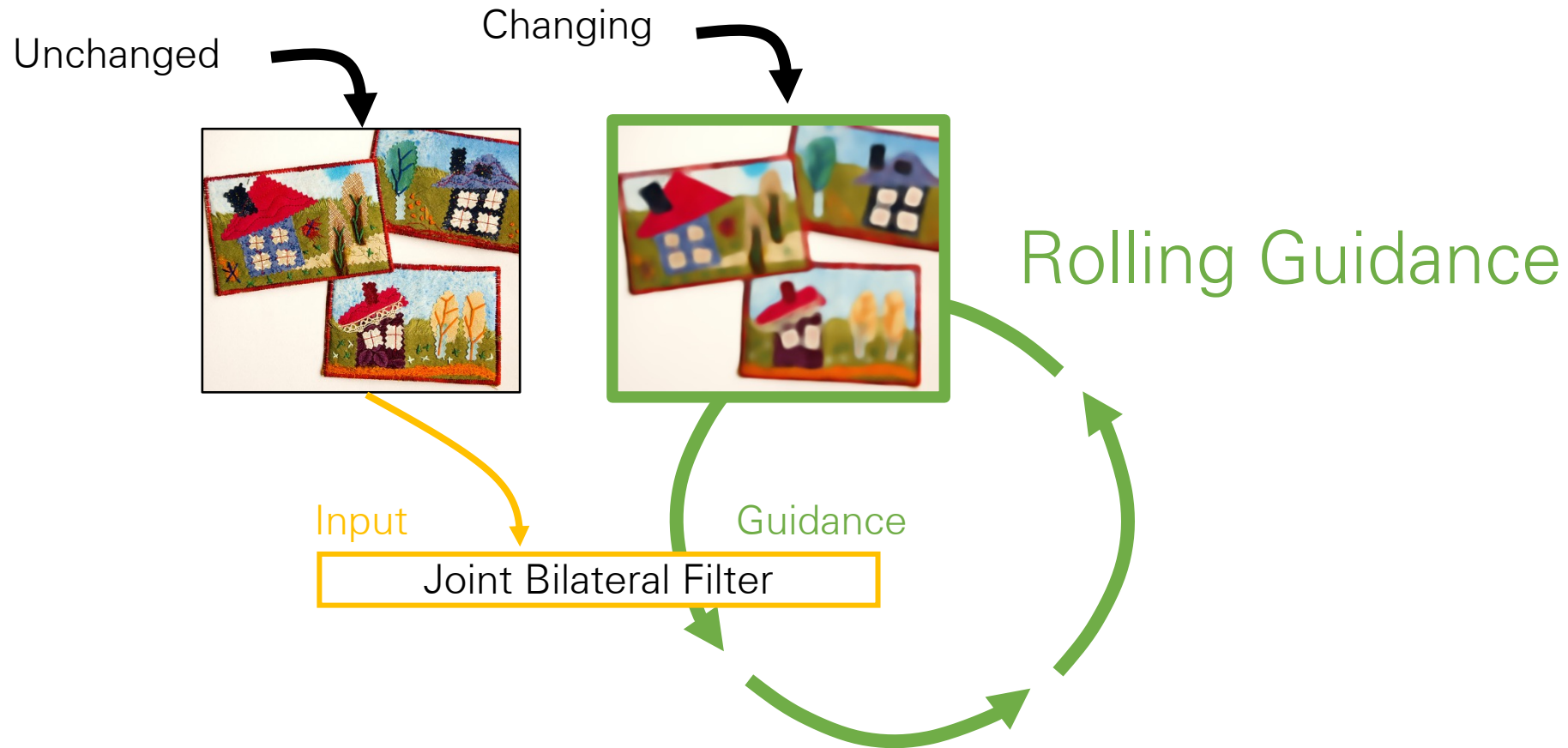


Step 2: Edge Recovery

- A rolling guidance



Rolling Guidance



Rolling Guidance



Guidance for the 1st
iteration

Rolling Guidance



Guidance for the 2nd iteration

Rolling Guidance



Guidance for the 3rd iteration

Rolling Guidance



Guidance for the 5th
iteration

Rolling Guidance



Input



Output



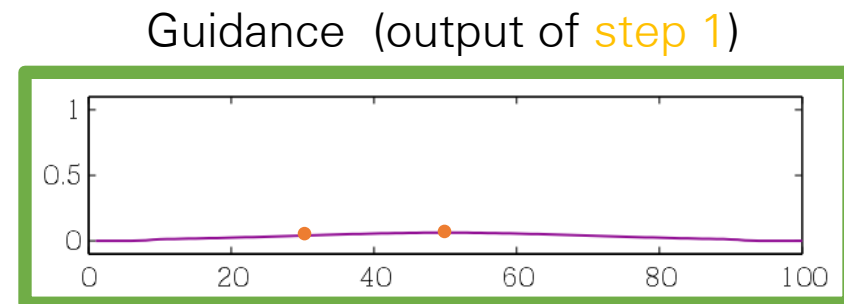
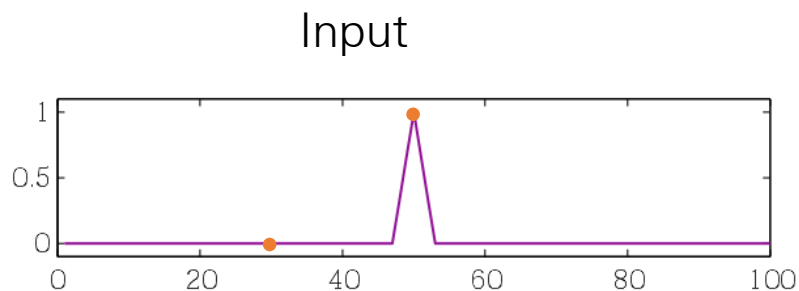
Small structures are **removed**.
Large structure are **NOT** blurred.

Implementation

Rolling Guidance Filter (RGF) has only **1 line** of code

```
1 Mat rollingGuidanceFilter(Mat im, float scale, int iter){  
2     Mat res = im.mul(0);  
3     while(iter-->0) res = bilateralFilter(im, res, scale, SIGMA_R);  
4     return res;  
5 }
```

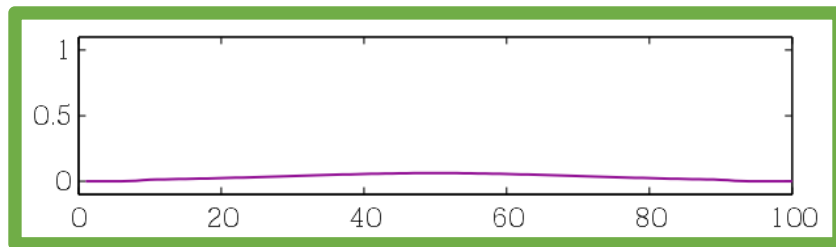
Small Structure



$$J^{t+1}(p) = \frac{1}{K_p} \sum_{q \in N(p)} \exp \left(- \frac{\|p - q\|^2}{2\sigma_s^2} \right)$$



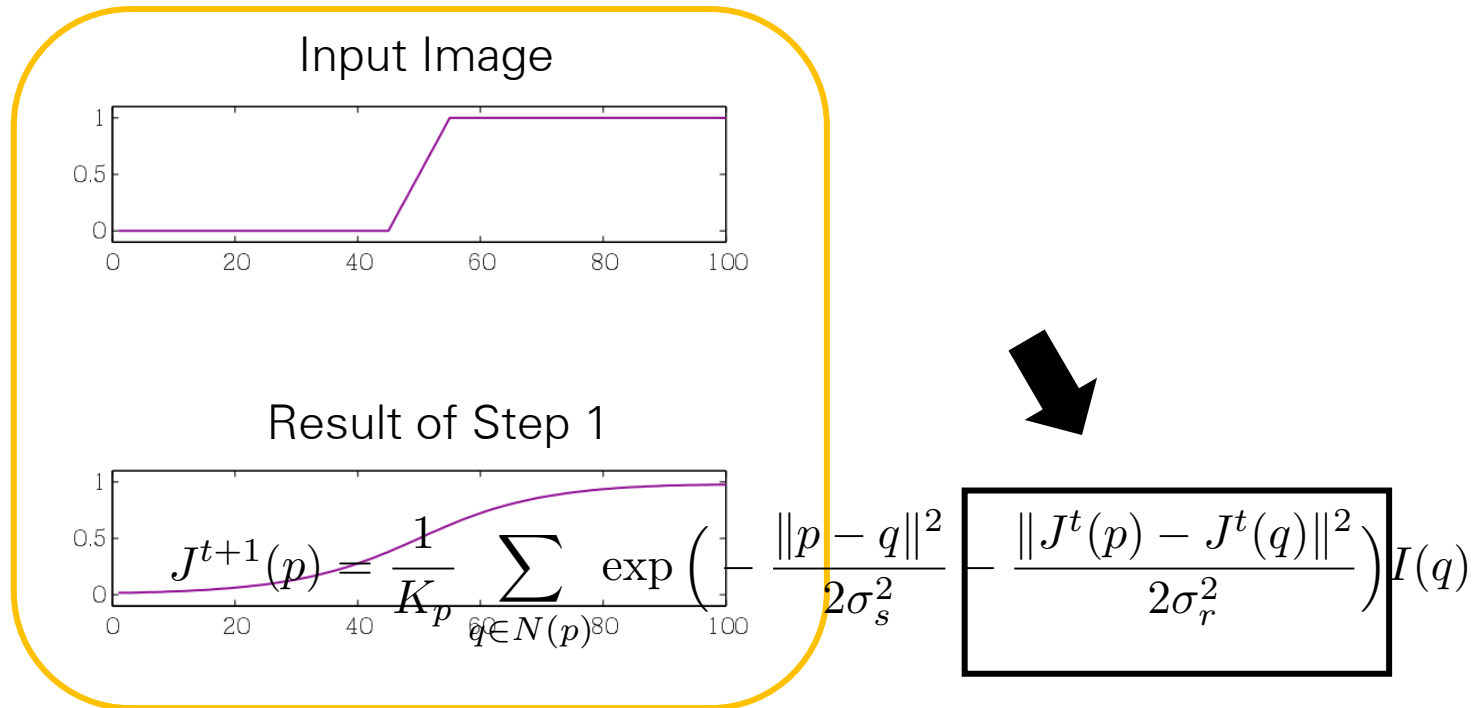
Joint Bilateral Filter



It becomes a Gaussian filter

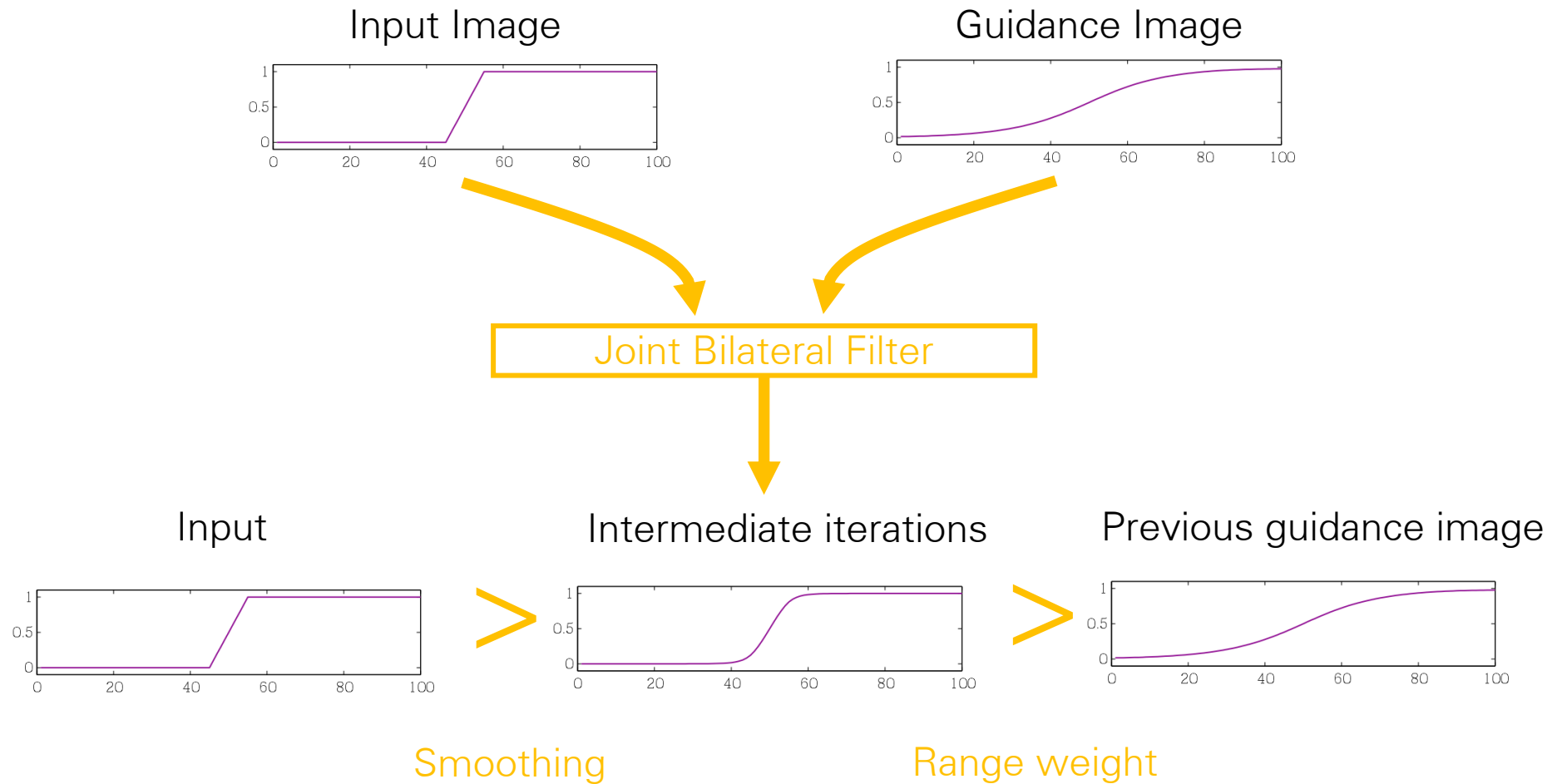
Same

Large Structure



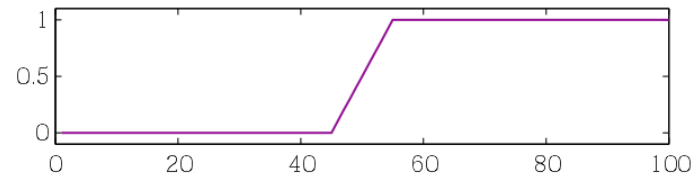
Due to this range weight
It generates sharper results than Gaussian!

Processing

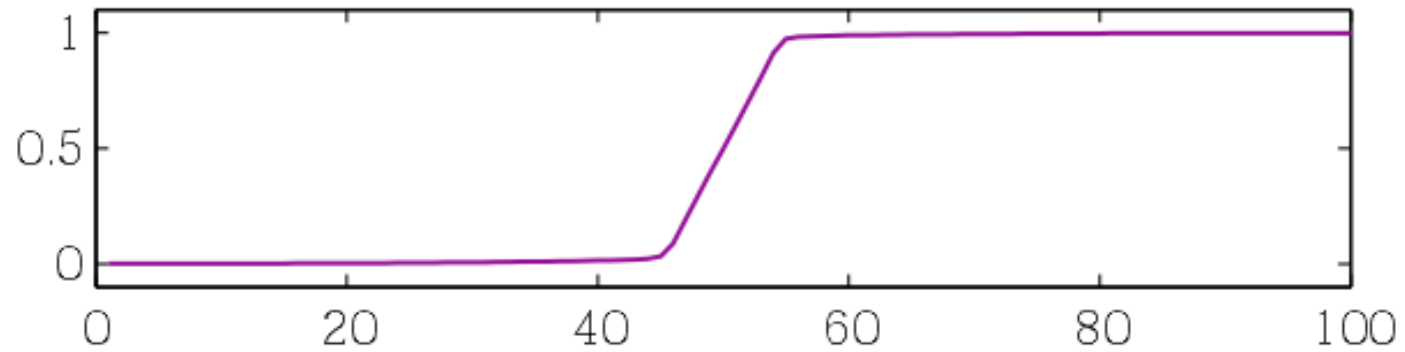


Processing

Input Image



Guidance Image



3rd Iteration

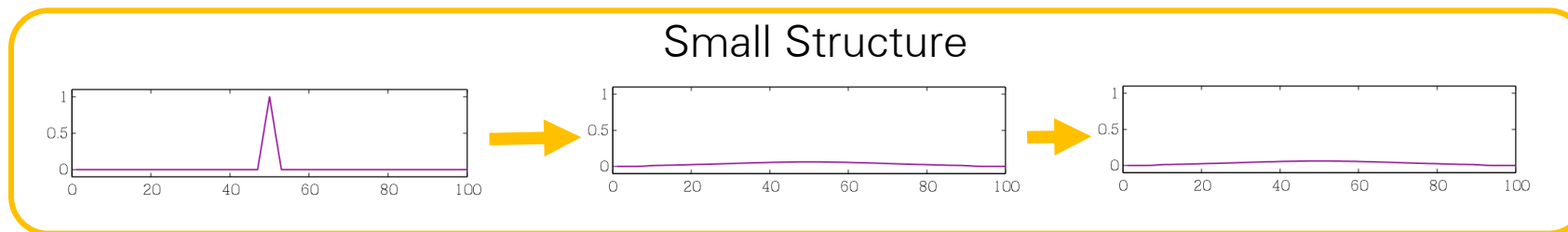
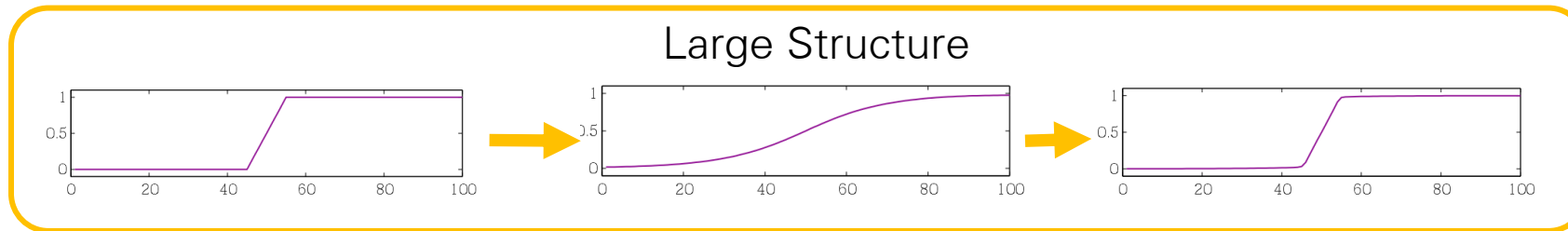
Large Structure



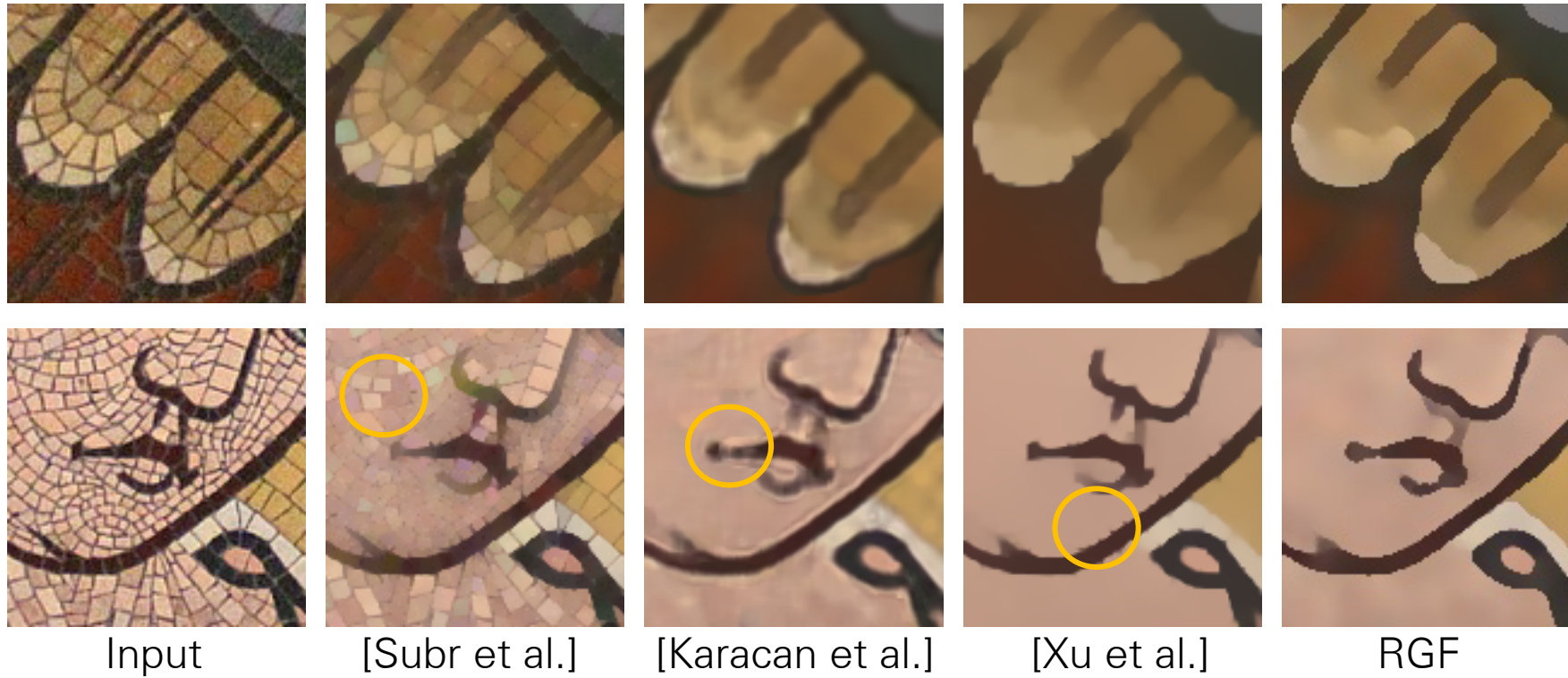
Take-home message

Rolling guidance recovers an edge as long as it still exists in the blurred image after Gaussian smoothing.

Rolling Guidance Filter



Result Comparison



Performance Comparison



Input

RGF
2013]

For 4 Megapixel Image

2

seconds

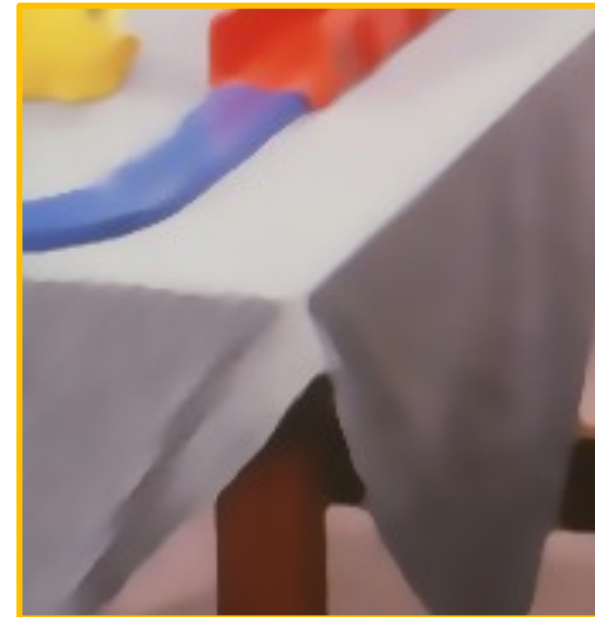
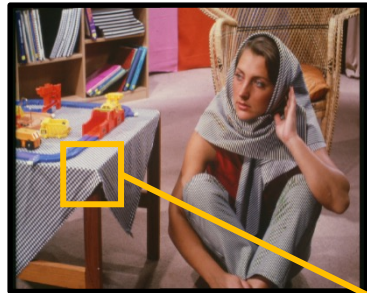
Performance Comparison

| Algorithms | Time (seconds/Megapixel) |
|--|--------------------------|
| Local Extrema [Subr et al., 2009] | 95 |
| RTV [Xu et al., 2012] | 14 |
| Region Covariance [Karacan et al., 2013] | 240 |
| RGF | 0.05(Real-time) |

Texture Removal



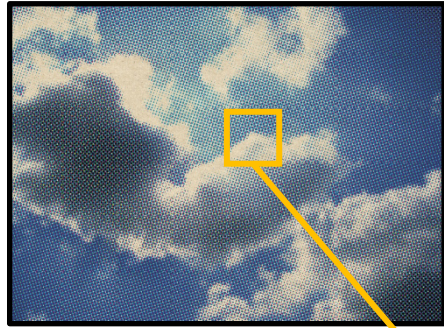
Texture Removal



Halftone Image



Halftone Image



Boundary detection

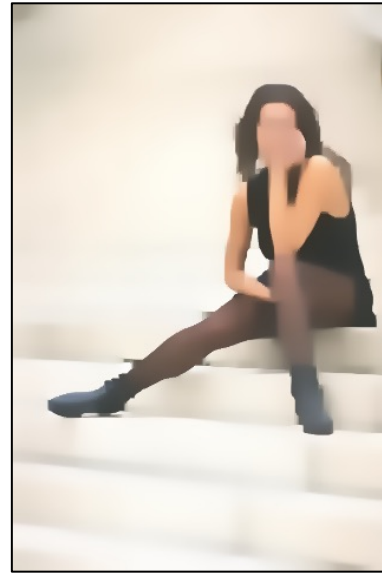
Input



Boundary Detection



Filtered Input



Boundary Detection



Multi-Scale Filtering



= 30

determine the scale.

Limitations

- Sharp corners could be rounded
 - It is because sharp corner presents high frequency change.
 - In other words, sharp corners are small-scale structures.

Recap

- Filtering plays a key role for many applications.
- Filtering by taking into account image content generally gives better results.

Next Lecture:
Gradient-domain image
processing