

Introduction to Computer Graphics

– Image Processing (1) –

July 1, 2021

Kenshi Takayama

Today's topics

- Edge-aware image processing



- Gradient-domain image processing

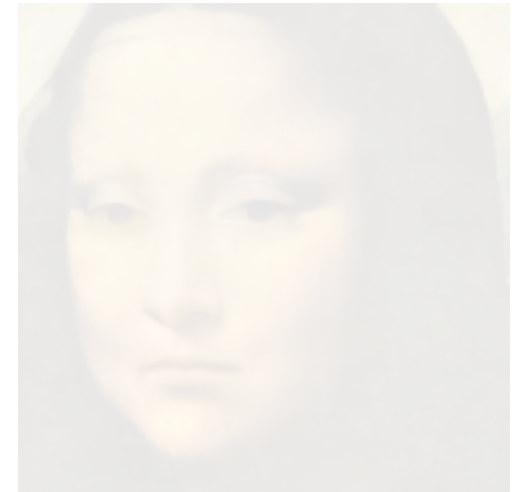
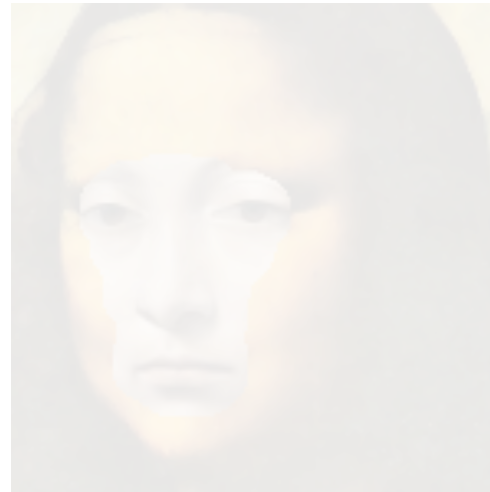


Image smoothing using Gaussian Filter

- Smoothness parameter σ



Original



$\sigma = 2$



$\sigma = 5$



$\sigma = 10$

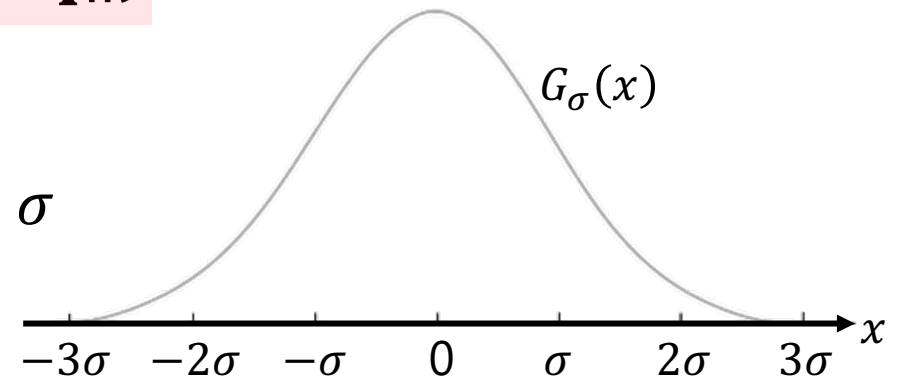
Equation of Gaussian Filter

- $I_{\mathbf{p}}$ represents pixel value of image I at position $\mathbf{p} = (p_x, p_y) \in \Omega$
 - For given resolution e.g. 640×480 , $\Omega := \{1, \dots, 640\} \times \{1, \dots, 480\}$
- $\text{GF}_{\sigma}[I]$ represents filtered image with Gaussian parameter σ :

$$\text{GF}_{\sigma}[I]_{\mathbf{p}} := \frac{\sum_{\mathbf{q} \in \Omega} G_{\sigma}(\|\mathbf{p} - \mathbf{q}\|) I_{\mathbf{q}}}{\sum_{\mathbf{q} \in \Omega} G_{\sigma}(\|\mathbf{p} - \mathbf{q}\|)}$$

$W_{\mathbf{p}}$

- $G_{\sigma}(x) := \exp\left(-\frac{x^2}{2\sigma^2}\right)$ ← Gaussian Kernel of radius σ

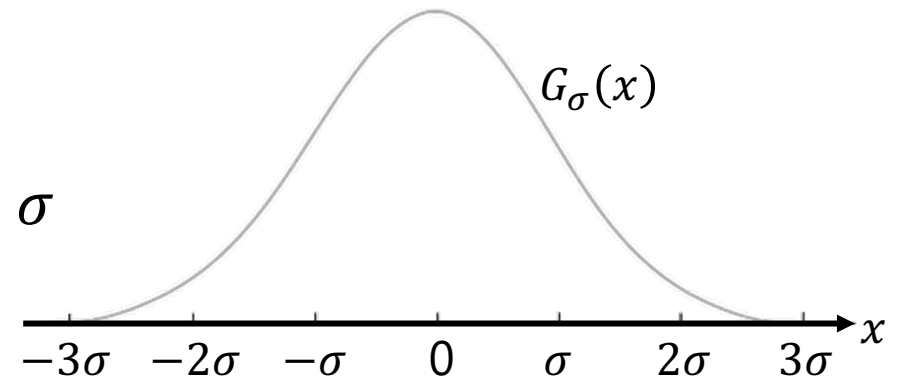


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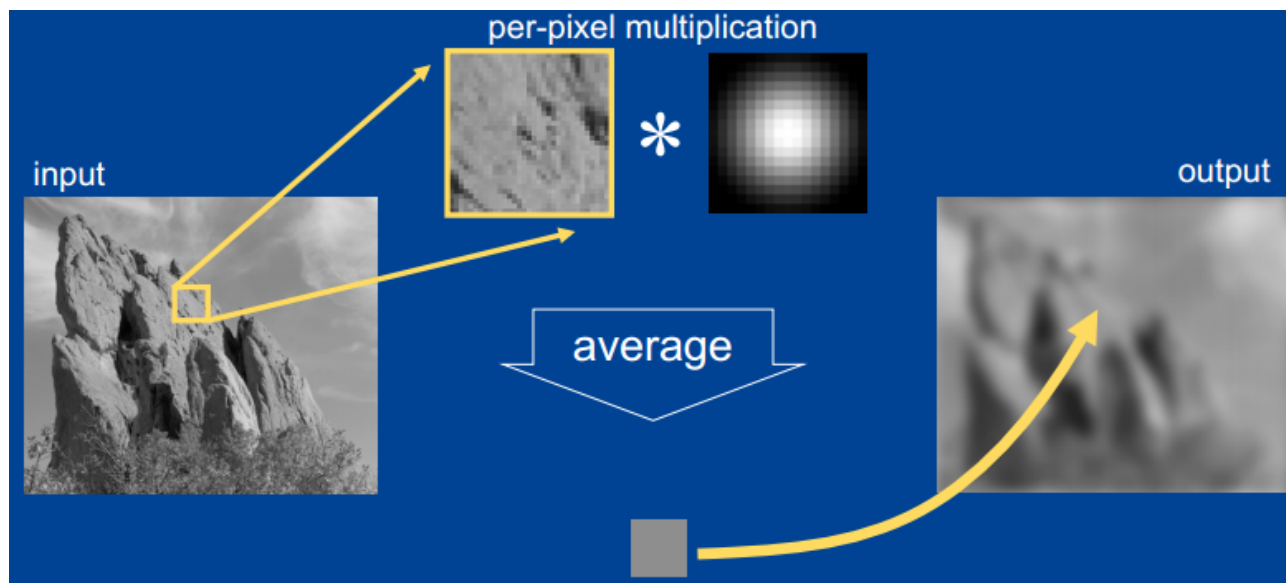
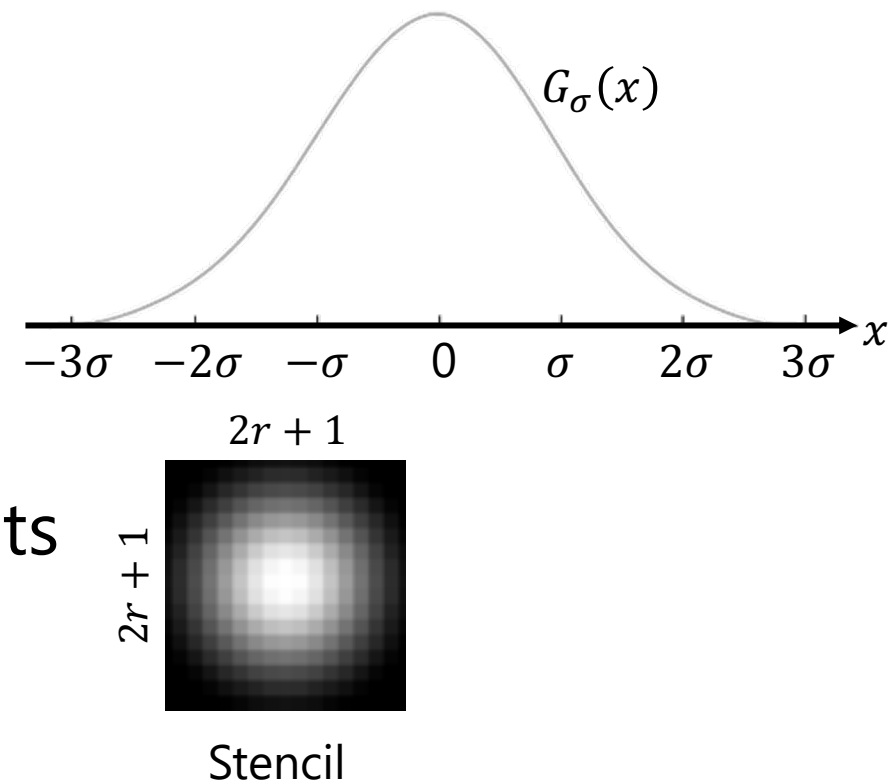
$$\text{GF}_{\sigma}[I]_{\mathbf{p}} := \frac{1}{W_{\mathbf{p}}} \sum_{\mathbf{q} \in \Omega} G_{\sigma}(\|\mathbf{p} - \mathbf{q}\|) I_{\mathbf{q}}$$

- $G_{\sigma}(x) := \exp\left(-\frac{x^2}{2\sigma^2}\right)$ ← Gaussian Kernel of radius σ



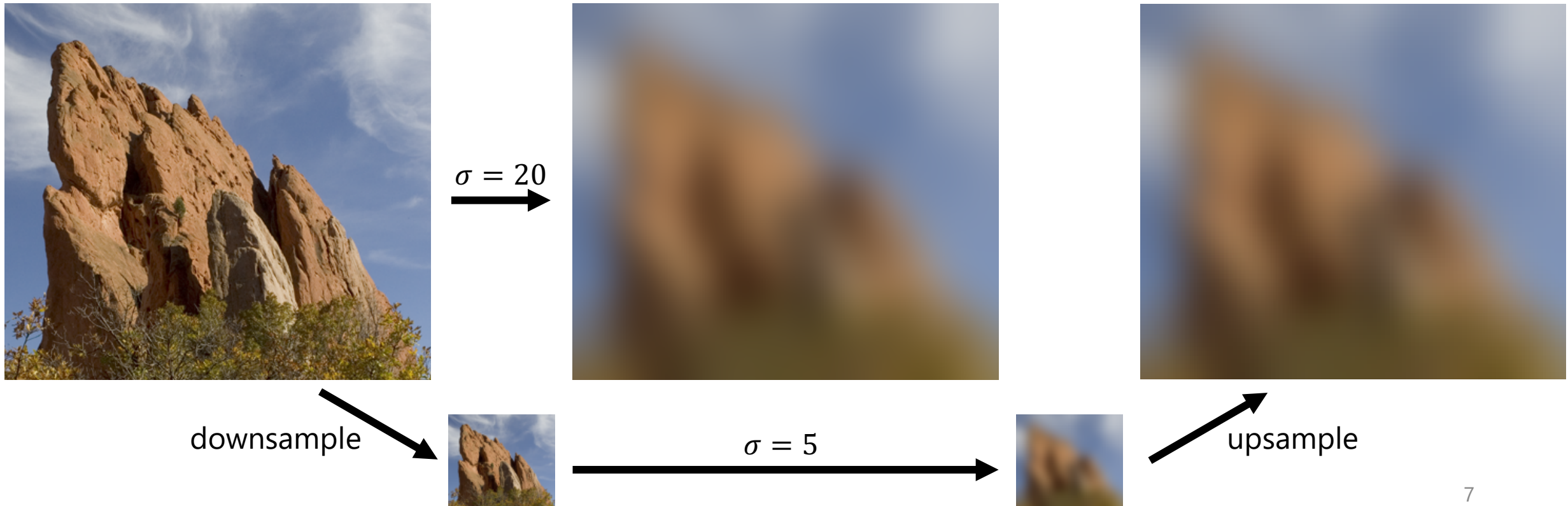
Implementing Gaussian Filter

- $G_\sigma(3\sigma) \approx 0 \rightarrow$ Distant pixels can be ignored
- For fixed size $r := \text{ceil}(3\sigma)$, precompute weights on a $(2r + 1) \times (2r + 1)$ stencil



When kernel radius σ is very large

- Direct computation takes a lot of time
- Alternative: downsample \rightarrow smooth with small σ \rightarrow upsample



Detail Extraction & Enhancement



-



smoothed

=



detail



+ 3x



detail

=



enhanced

When using edge-aware smoothing, ...

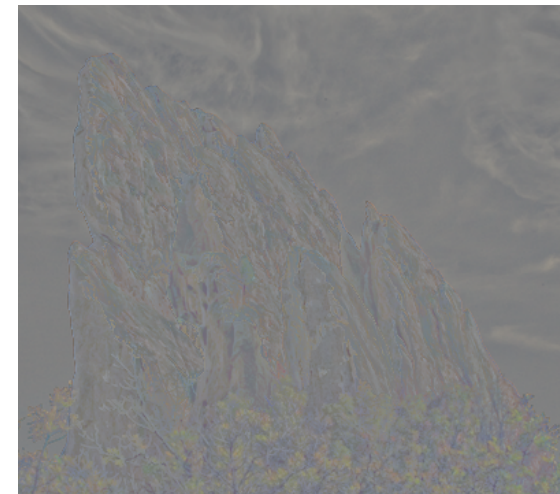


-



smoothed

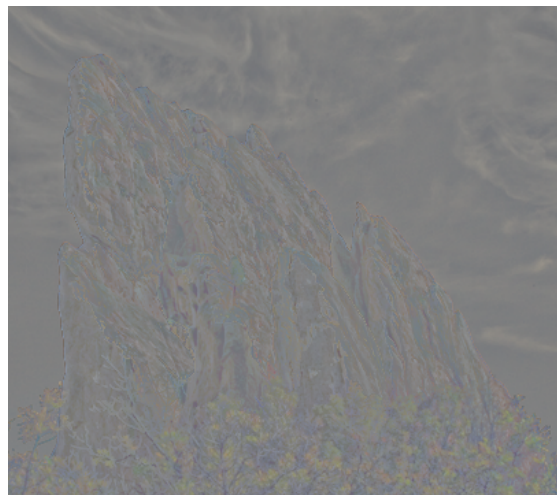
=



detail



+ 3x



detail

=



enhanced

Edge-aware smoothing using **Bilateral Filter**

- Two parameters
 - σ_s : Range of smoothing w.r.t. pixel's **location**
 - σ_r : Range of smoothing w.r.t. pixel's **color**

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

In all cases, $\sigma_s = 10$



Original



$\sigma_r = 32$



$\sigma_r = 128$



$\sigma_r = 512_{10}$

Application of Bilateral Filter: Stylization

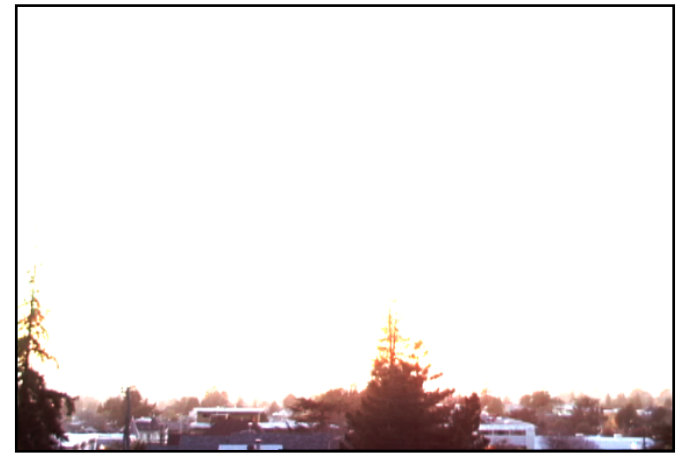
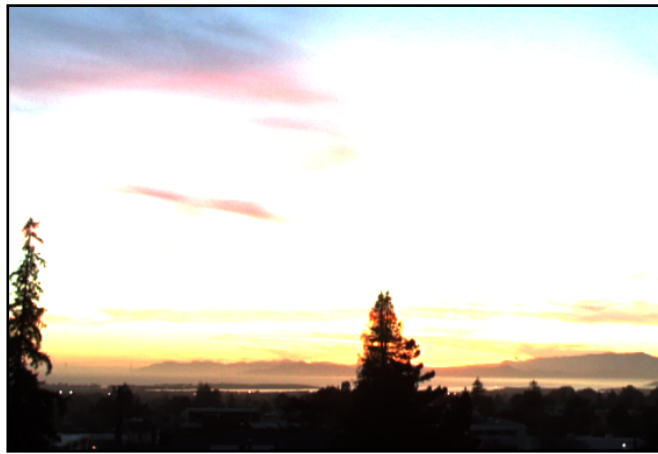


Application of Bilateral Filter: Tone Mapping

- Range of each channel (24bit color image): 1~255
- Range of light intensity in the real world: 1~10⁵
 - **H**igh **D**ynamic **R**ange image
 - Can be obtained by photographing with different exposure times

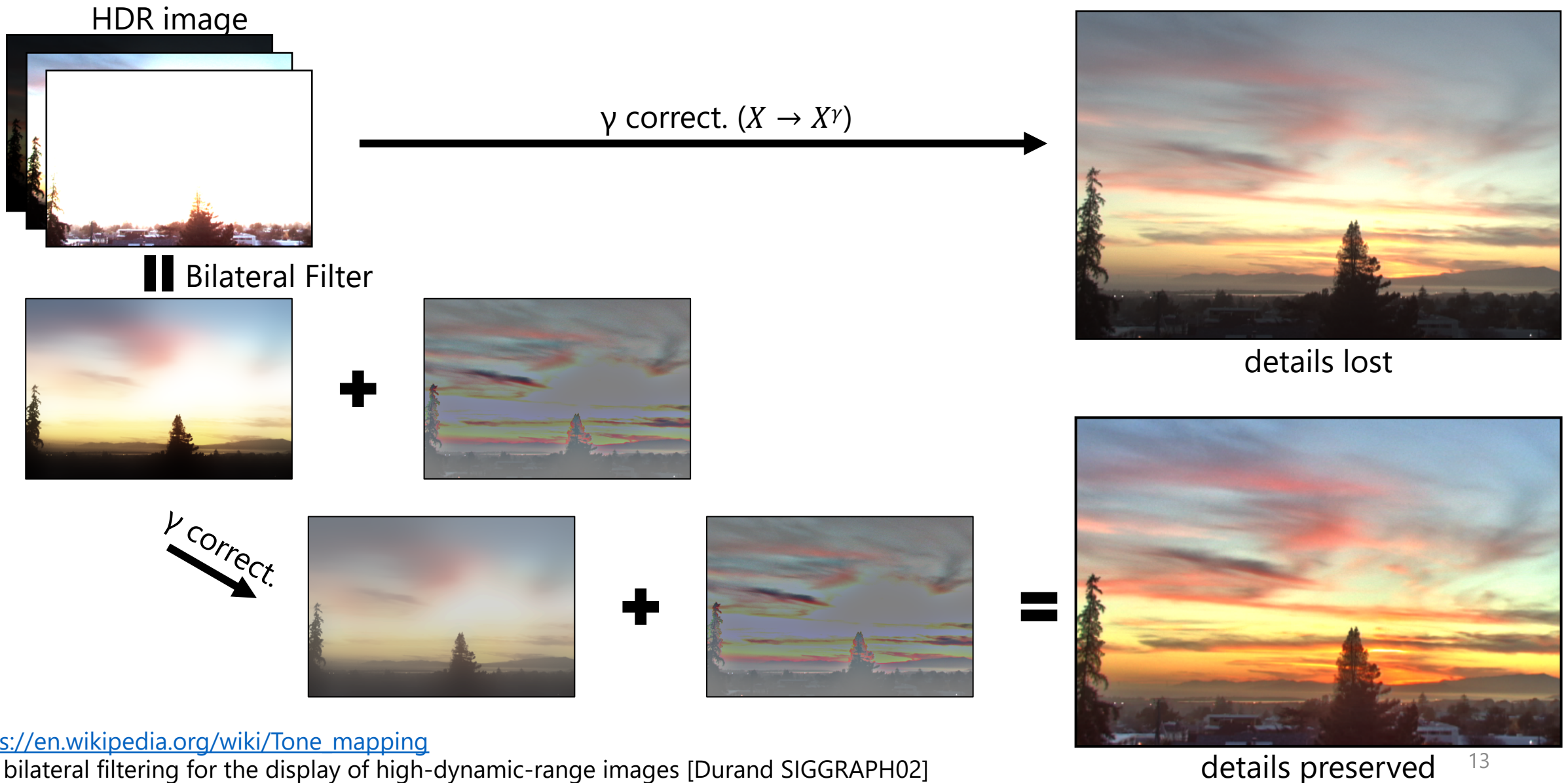


Short exposure



Long exposure

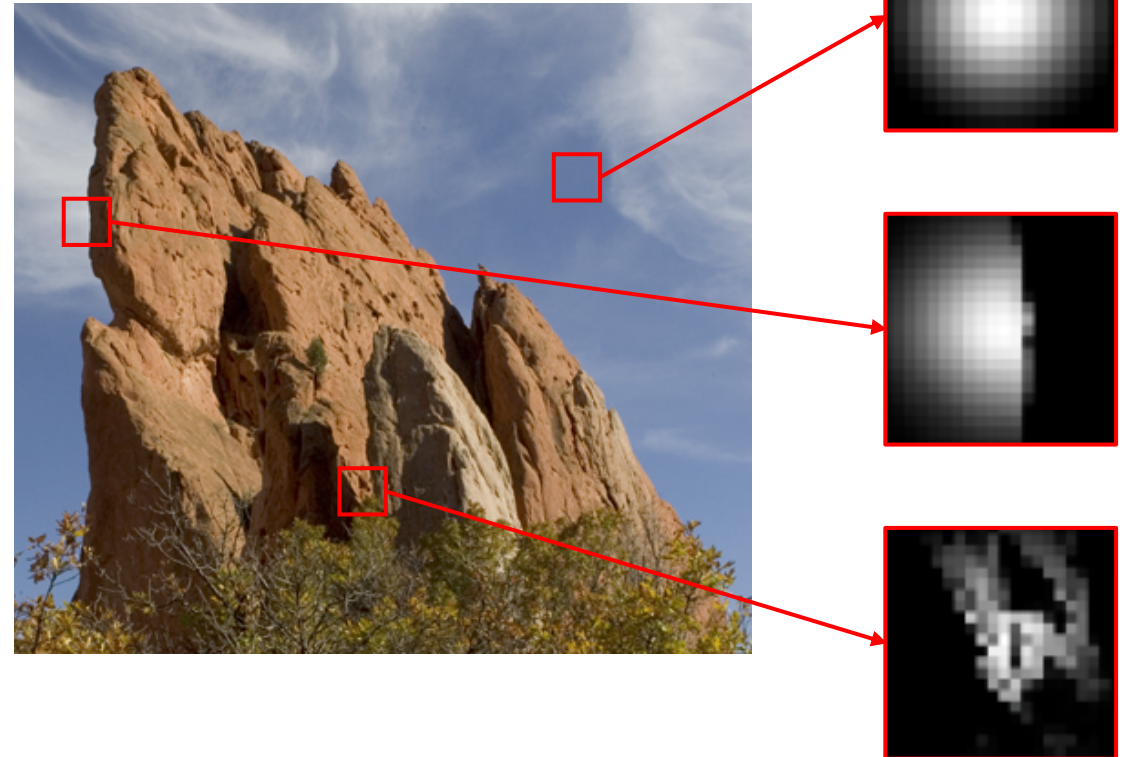
Application of Bilateral Filter: Tone Mapping



Naïve implementation of Bilateral Filter

$$\frac{1}{W_p} \sum_{q \in \Omega} G_{\sigma_s}(\|\mathbf{p} - \mathbf{q}\|) G_{\sigma_r}(\|I_p - I_q\|) I_q$$

- Recompute stencil for every pixel location $\mathbf{p} \in \Omega$
→ slow
- (Basic Assignment)



Another view toward Bilateral Filter

- Define **feature vector** $\mathbf{f}_p := \left(\frac{\mathbf{p}}{\sigma_s}, \frac{I_p}{\sigma_r} \right)$ for pixel location \mathbf{p} and intensity I_p

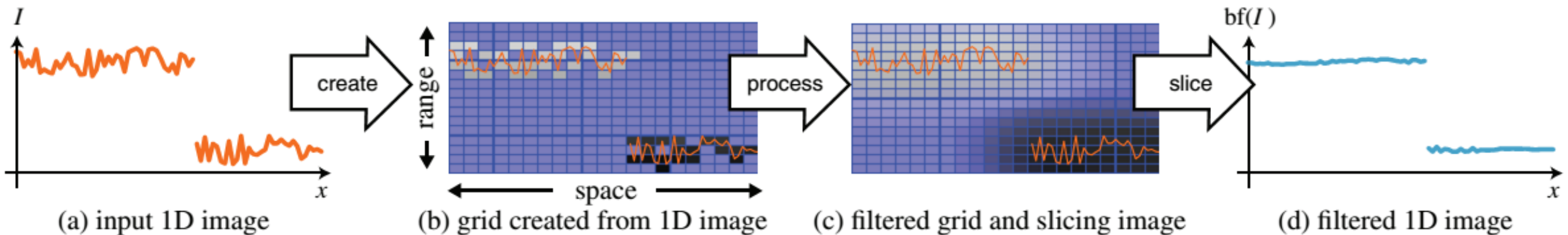
- Weight of Bilateral Filter is equivalent to Gaussian kernel applied to Euclidean distance in the feature space

$$\begin{aligned} & G_{\sigma_s}(\|\mathbf{p} - \mathbf{q}\|) G_{\sigma_r}(\|I_p - I_q\|) \\ &= \exp\left(-\frac{\|\mathbf{p} - \mathbf{q}\|^2}{2\sigma_s^2}\right) \exp\left(-\frac{\|I_p - I_q\|^2}{2\sigma_r^2}\right) \\ &= \exp\left(-\frac{\|\mathbf{f}_p - \mathbf{f}_q\|^2}{2}\right) \\ &= G_1(\|\mathbf{f}_p - \mathbf{f}_q\|) \end{aligned}$$

- Bilateral Filter is equivalent to applying Gaussian Filter of radius 1 to sample points $\{\mathbf{f}_p\}$ in the feature space
→ Simpler computation

Bilateral Grid [Paris06; Chen07]

- Define 3D feature space as (X-coord, Y-coord, intensity), map sample points $\{f_p\}$ to 3D grid
- The larger σ_s & σ_r , the coarser the grid \rightarrow lower comput. cost



Weight map generation using feature space



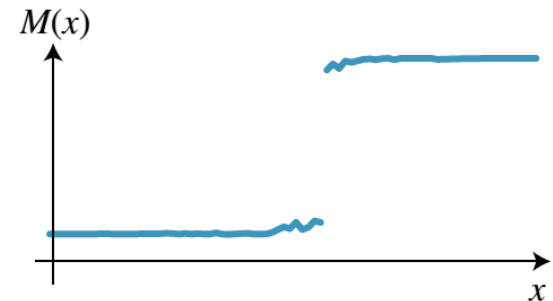
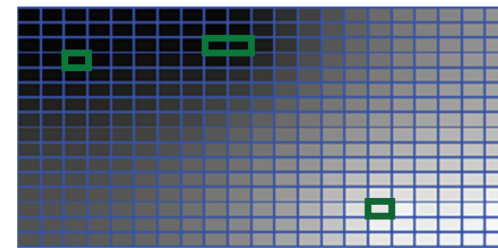
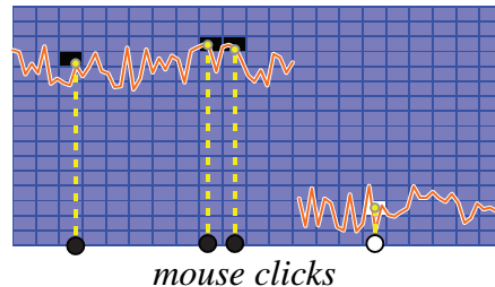
White scribble → constraint of weight=1
Black scribble → constraint of weight=0

Weight map

Application: color adjustment

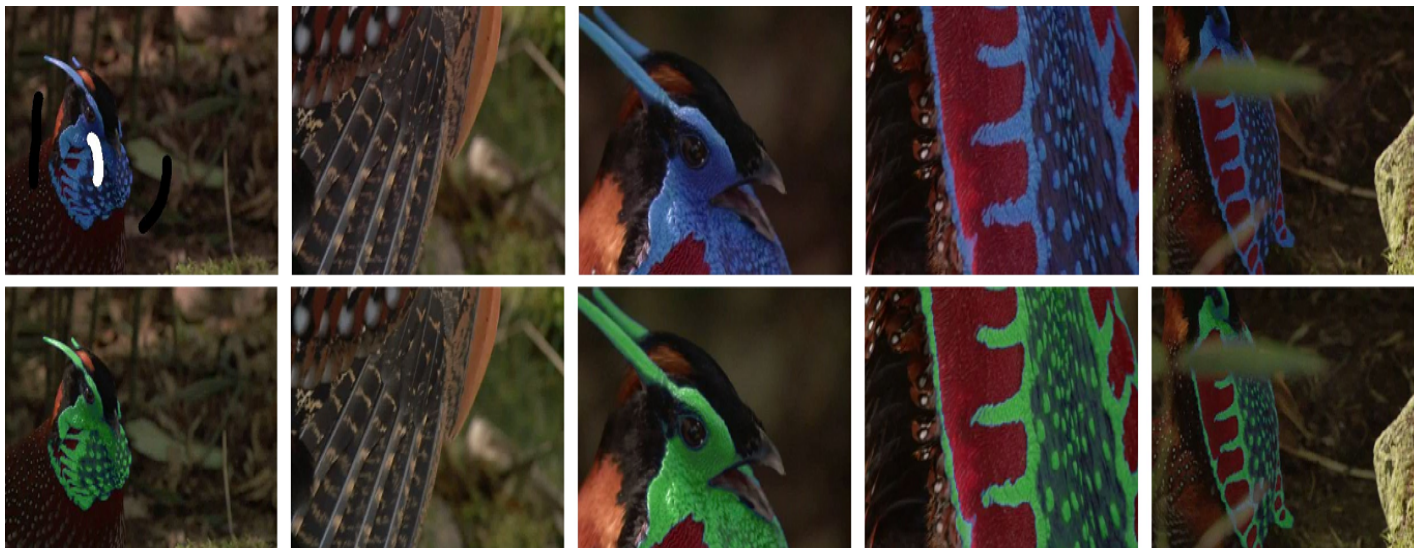
- Various names: Edit Propagation, Matting, Segmentation

- Solve Laplace equation on Bilateral Grid




Weight map generation using feature space


Interpolation using RBF [Li10]
(Purpose: edit propagation for images/videos)



Interpolation using Hermite RBF [Ijiri13]
(Purpose: segmentation of CT volume)

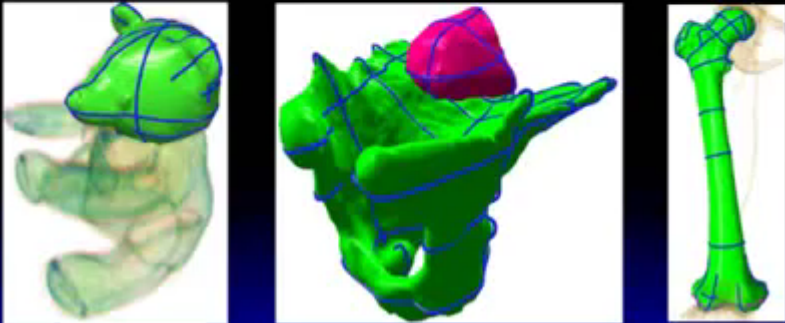


Eurographics 2013
May 6-10, Girona (Spain)



**Bilateral Hermite Radial Basis Functions for
Contour-based Volume Segmentation**

T. Ijiri¹, S. Yoshizawa¹, Y. Sato², M. Ito², H. Yokota¹
¹RIKEN, ²National Cancer Center Hospital East



https://www.youtube.com/watch?v=mL6ig_OaQAA

Extension to BF: Joint (Cross) Bilateral Filter



Photo A: without flash

☺ Correct color

☹ Noisy, blurred



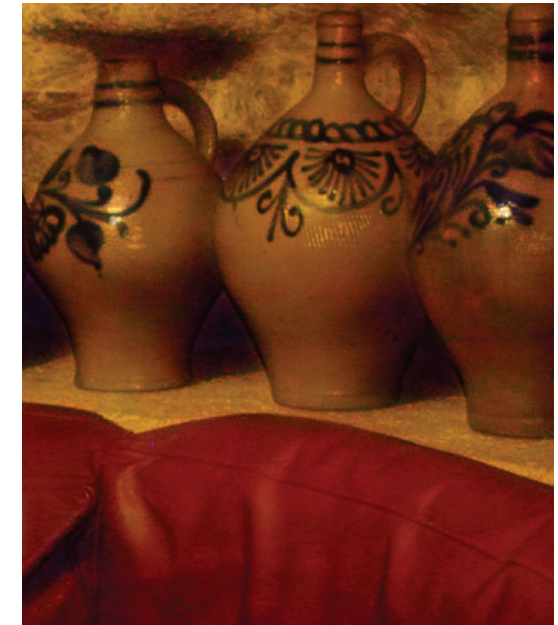
Photo F: with flash

☹ Incorrect color

☺ Less noisy, sharp

$$\text{JBF}_{\sigma_s, \sigma_r}(A, F)_{\mathbf{p}} := \frac{1}{W_{\mathbf{p}}} \sum_{\mathbf{q} \in \Omega} G_{\sigma_s}(\|\mathbf{p} - \mathbf{q}\|) G_{\sigma_r}(\|F_{\mathbf{p}} - F_{\mathbf{q}}\|) A_{\mathbf{q}}$$

After applying JBF



Extension to BF: Non-Local Means Filter

- Define feature space by **neighborhood vector** \mathbf{n}_p representing 7×7 sub-image centered at \mathbf{p}

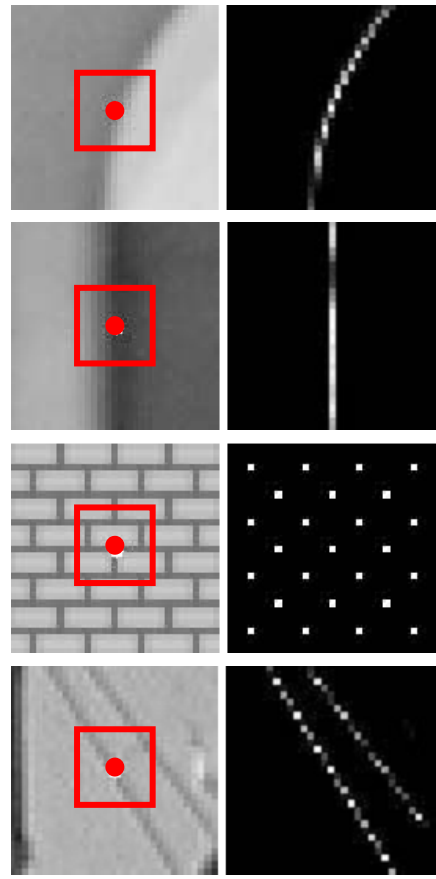
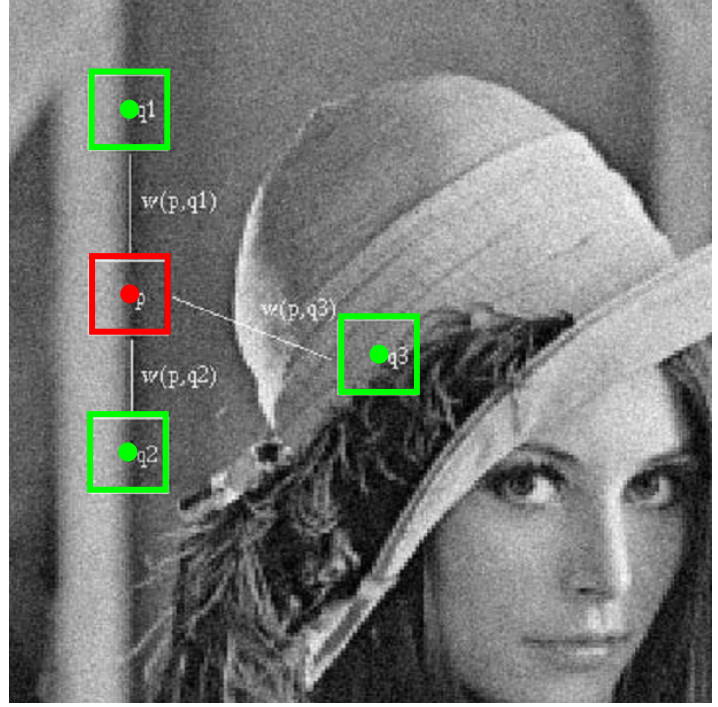
$$NLMF_{\sigma}(I)_p := \frac{1}{W_p} \sum_{q \in \Omega} G_{\sigma}(\|\mathbf{n}_p - \mathbf{n}_q\|) I_q$$



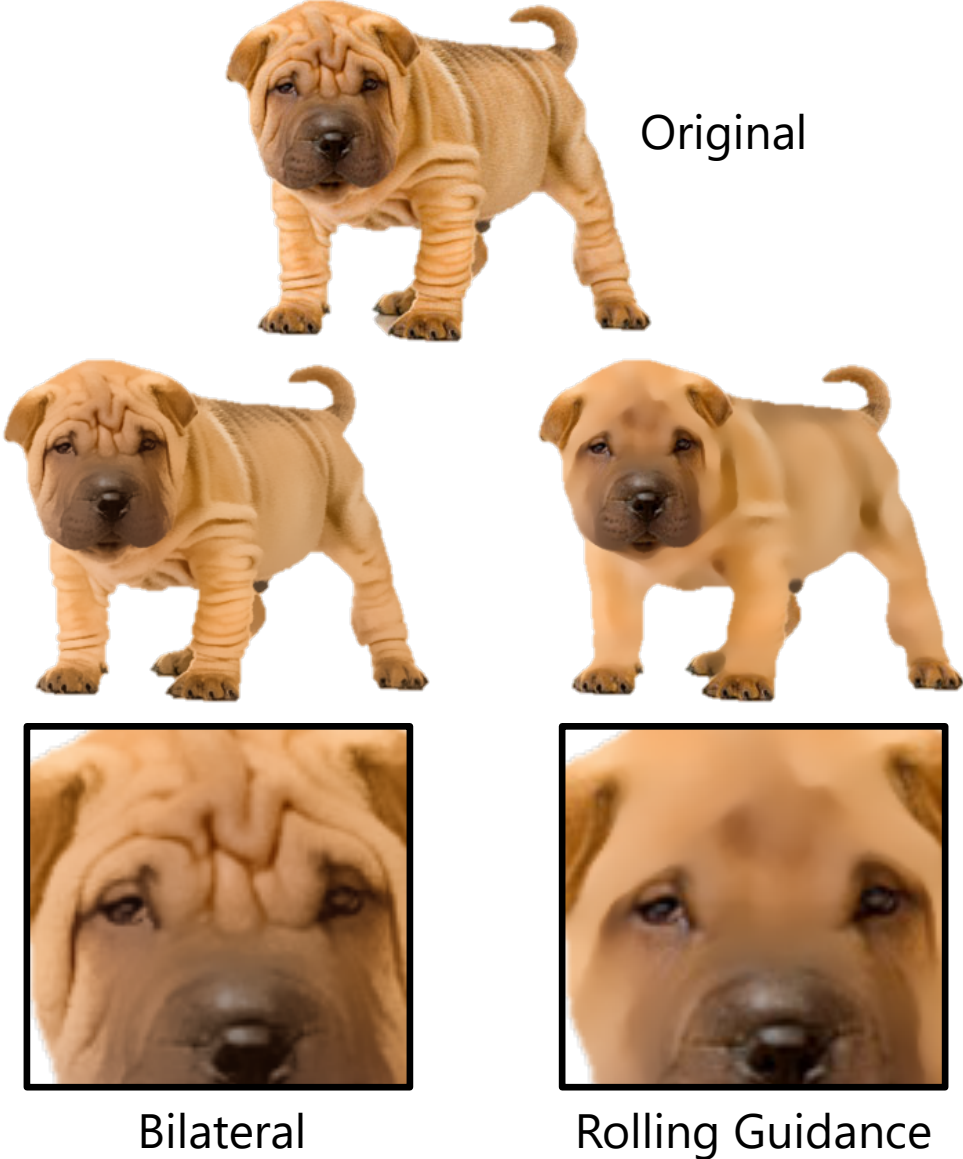
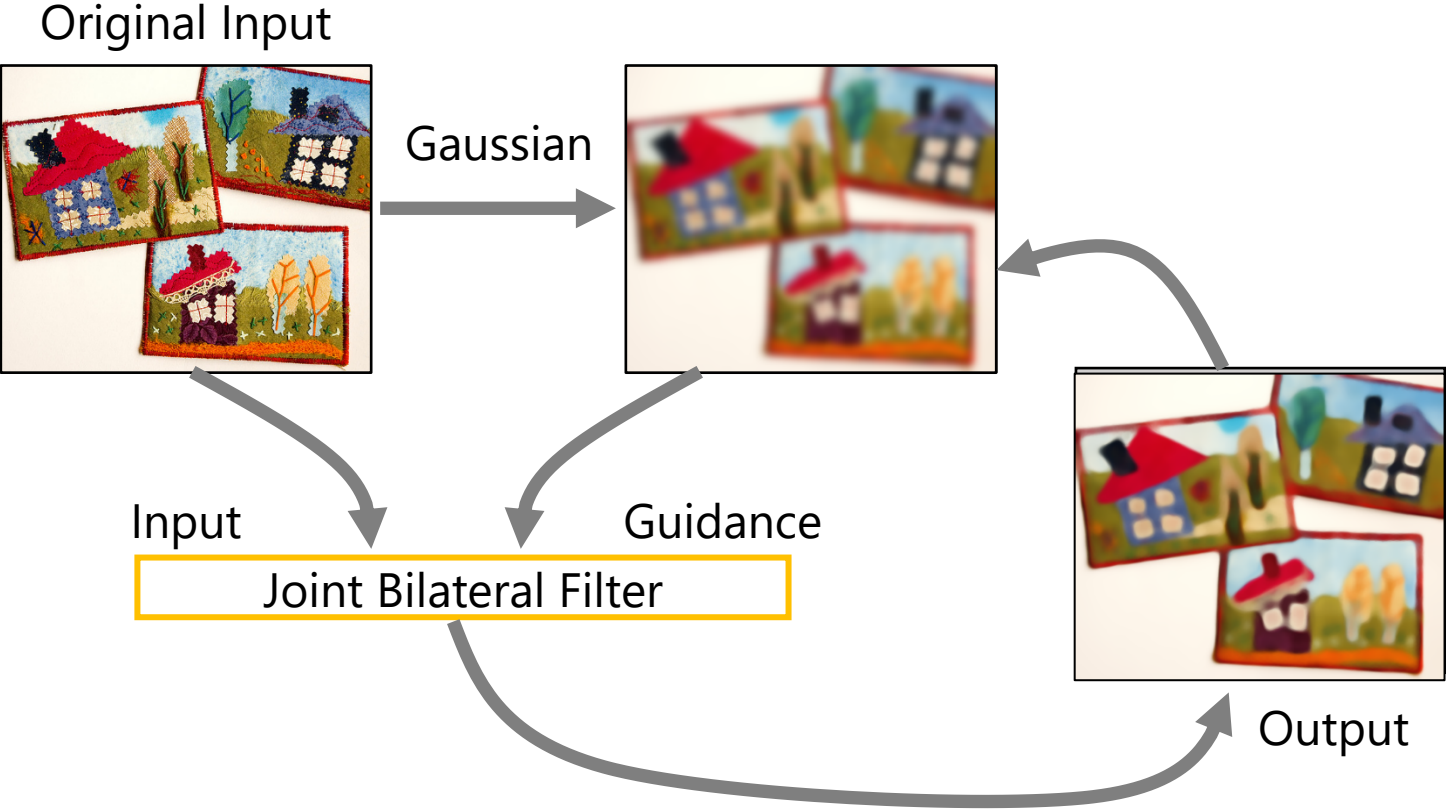
Noisy input

Bilateral

NL Means

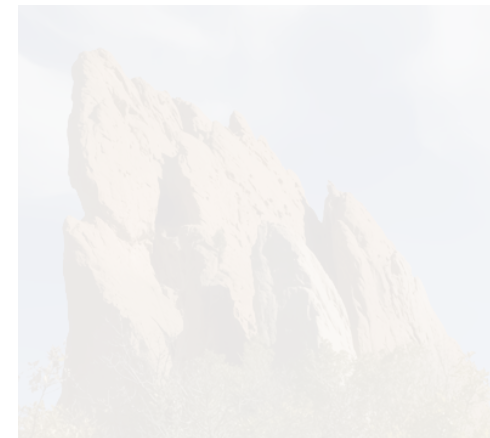
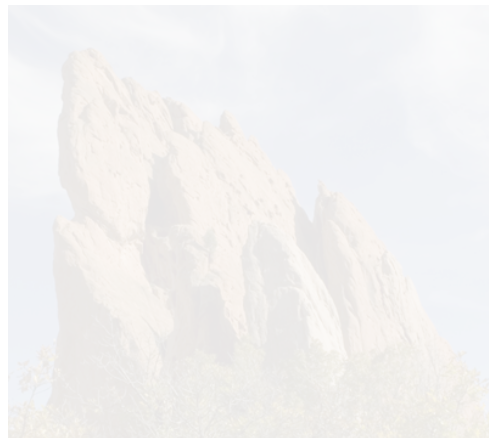


Extension to BF: Rolling Guidance Filter



Today's topics

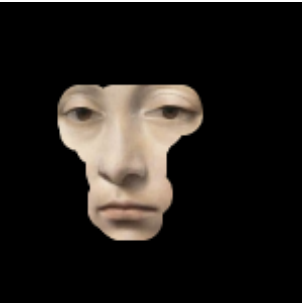
- Edge-aware image processing



- Gradient-domain image processing



Scenario: insert source img. into destination img.



Source



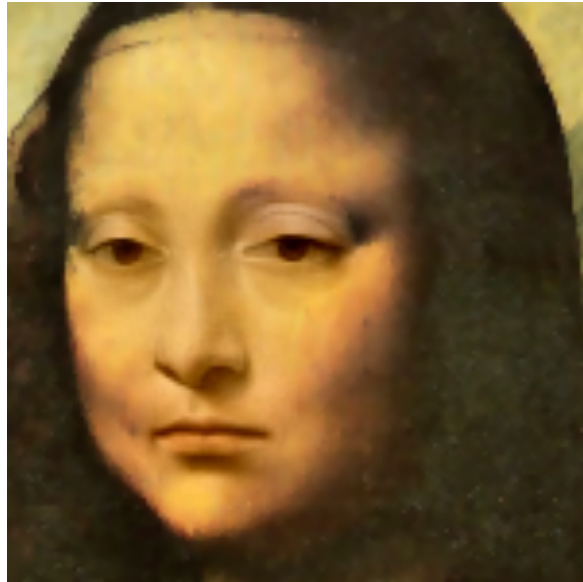
Dest.



Simple copying
☹️

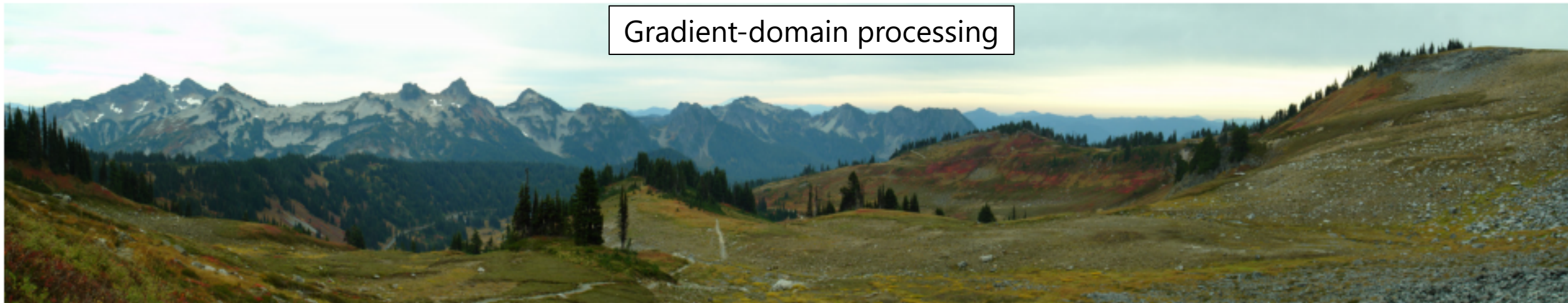


Boundary blurred
☹️

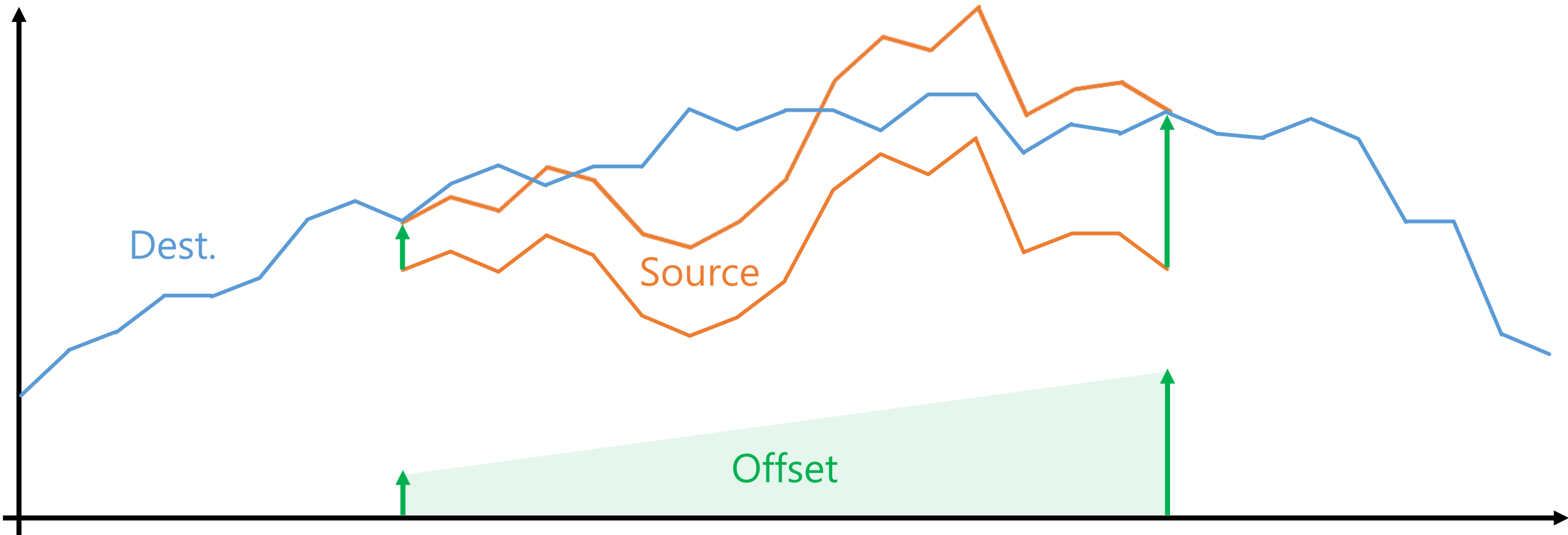


Gradient-domain processing
😊

Scenario: generating panorama from several shots



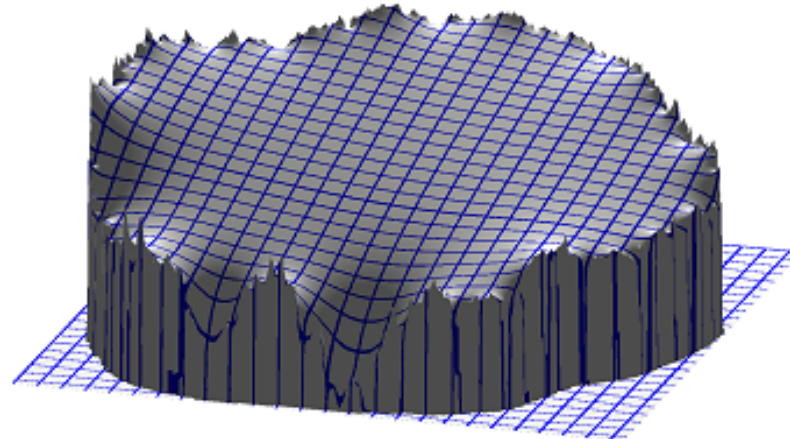
Simple case of 1D grayscale image



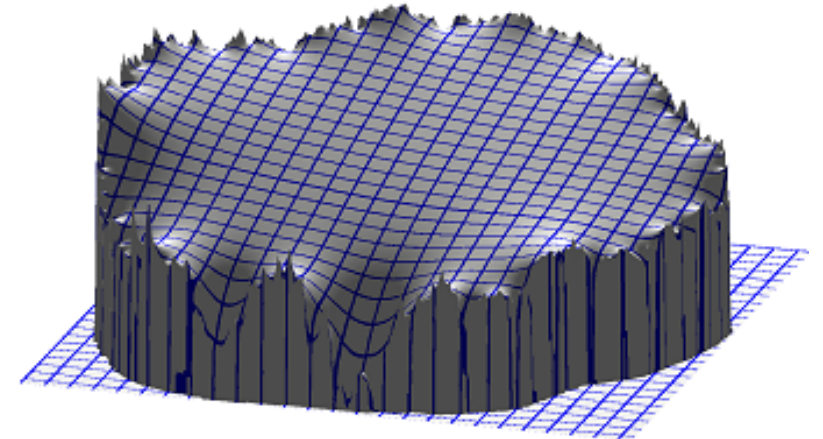
2D case: offset by Laplace Membrane



(a) Source patch

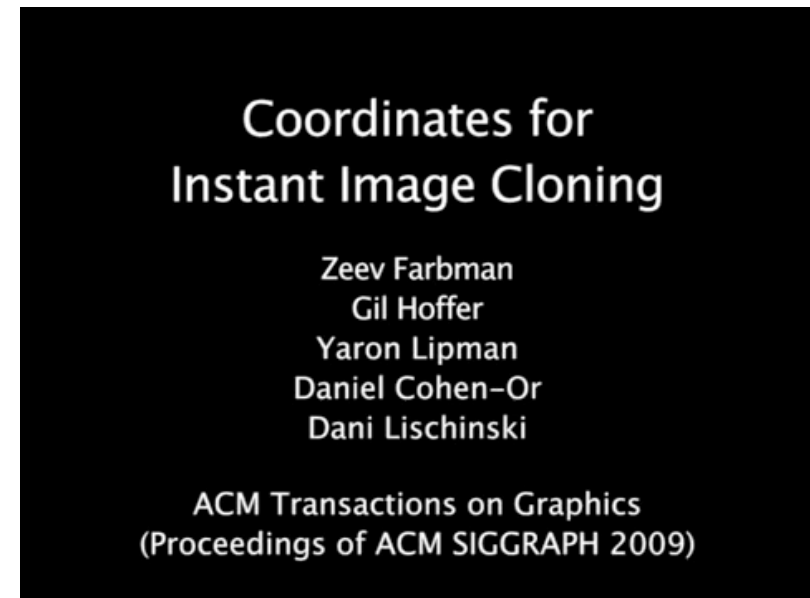


(b) Laplace membrane

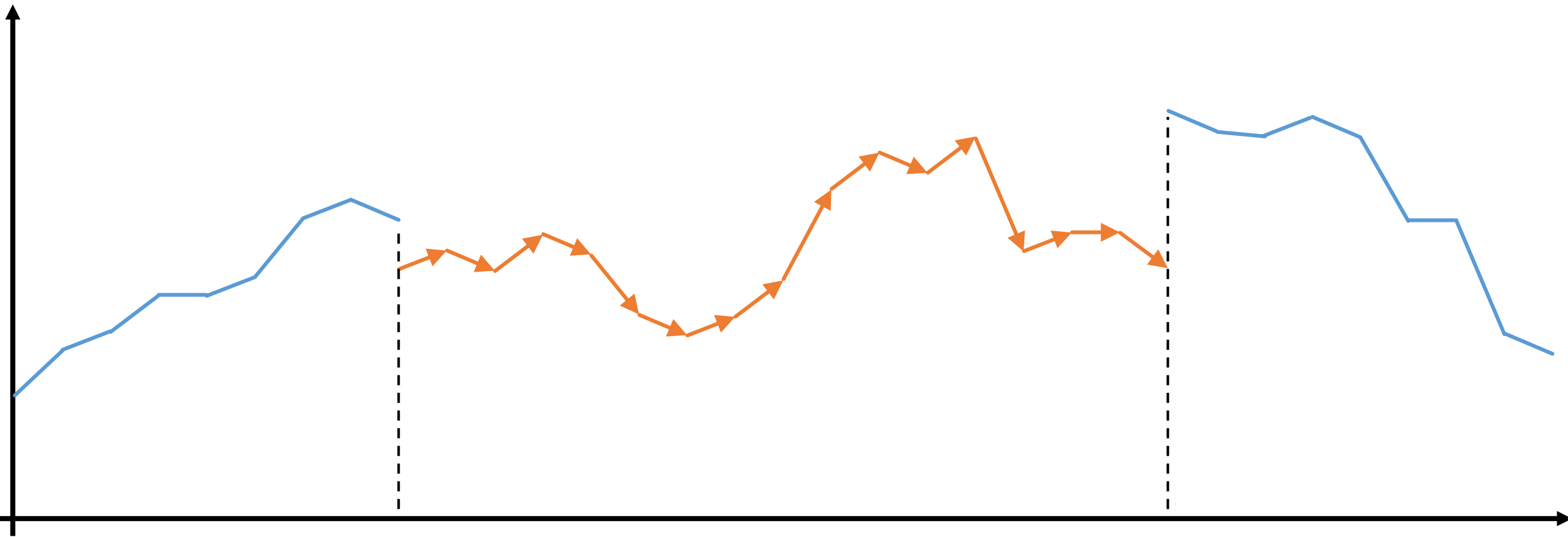


(c) Mean-value membrane

- Solve Laplace equation under Dirichlet boundary condition
- Fast approximation using Mean Value Coordinates

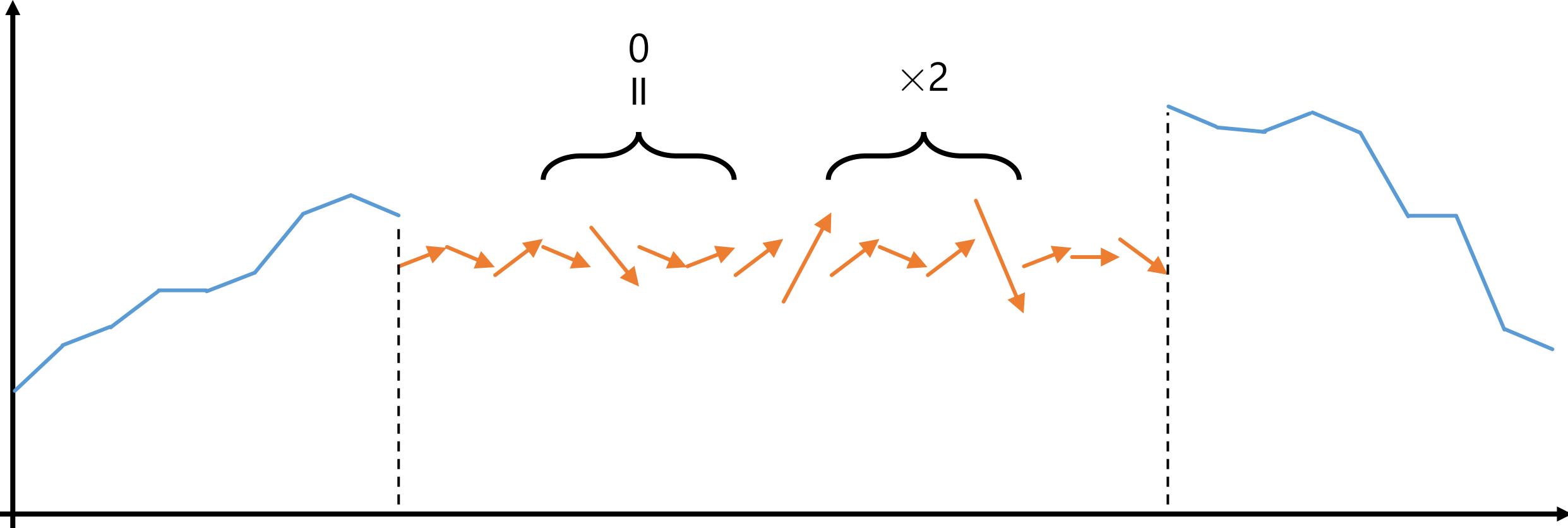


Gradient-domain processing in general form (not just simple cloning)



Gradient-domain processing in general form (not just simple cloning)

Modify gradients arbitrarily!

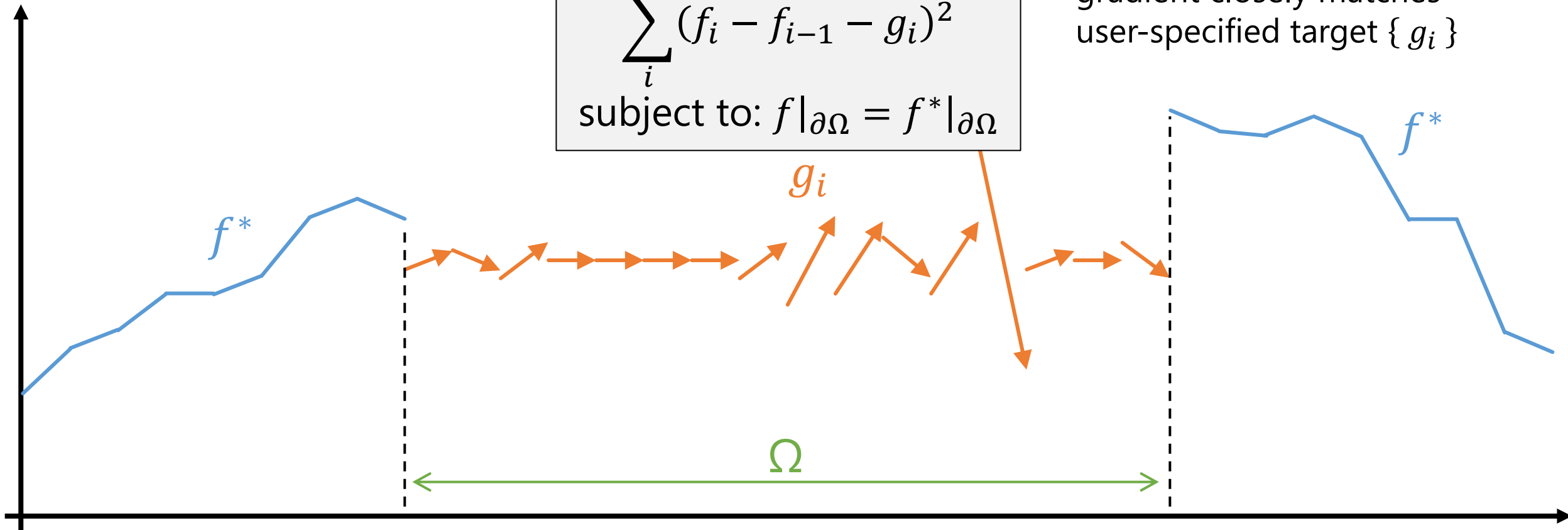


Gradient-domain processing in general form (not just simple cloning)

Find $\{f_i\}$ that minimize
$$\sum_i (f_i - f_{i-1} - g_i)^2$$

subject to: $f|_{\partial\Omega} = f^*|_{\partial\Omega}$

Find function f such that its
gradient closely matches
user-specified target $\{g_i\}$



1D case

Find $\{f_i\}$ that minimize

$$\sum_i (f_i - f_{i-1} - g_i)^2$$

subject to: $f|_{\partial\Omega} = f^*|_{\partial\Omega}$

2D case

Find $f(x, y)$ that minimizes

$$\int_{(x,y) \in \Omega} \|\nabla f(x, y) - \mathbf{g}(x, y)\|^2$$

subject to: $f|_{\partial\Omega} = f^*|_{\partial\Omega}$



- Basics of Gradient-domain image processing:

Find image f whose gradient best matches user-specified target gradient field \mathbf{g} by solving Poisson equation

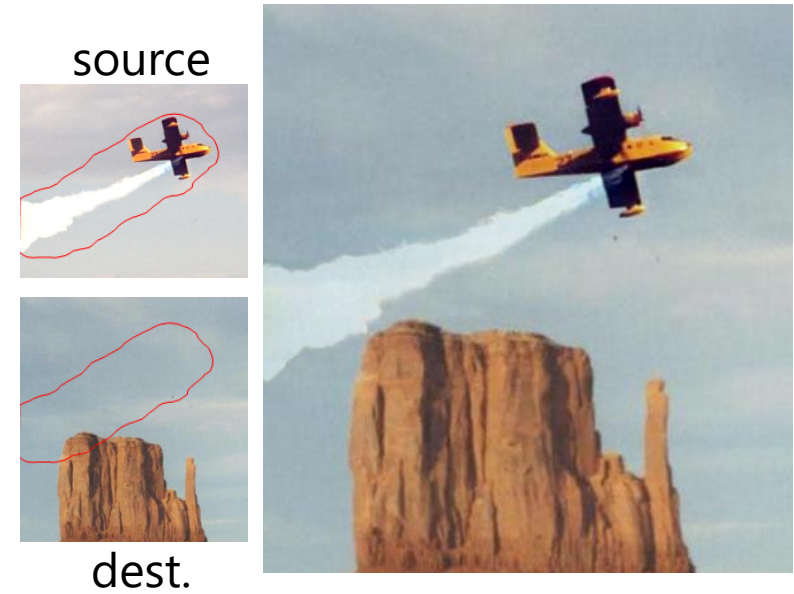
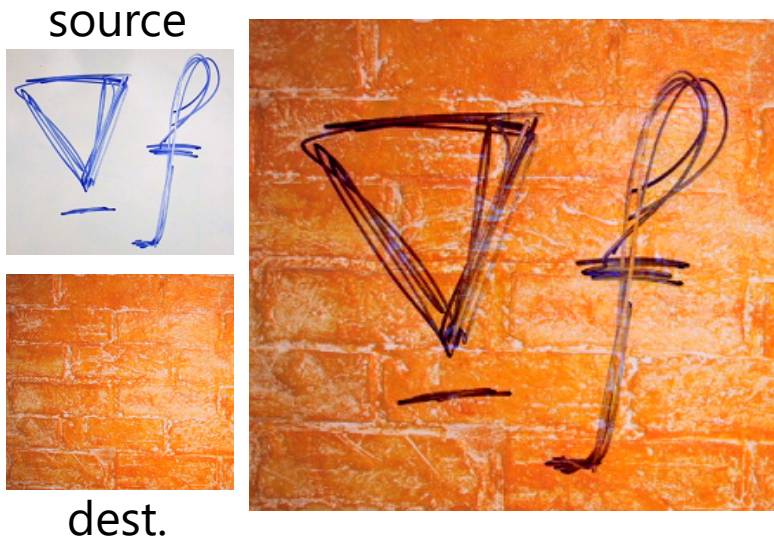
Solve **Poisson equation**:

$$\Delta f = \nabla \cdot \mathbf{g}$$

subject to: $f|_{\partial\Omega} = f^*|_{\partial\Omega}$

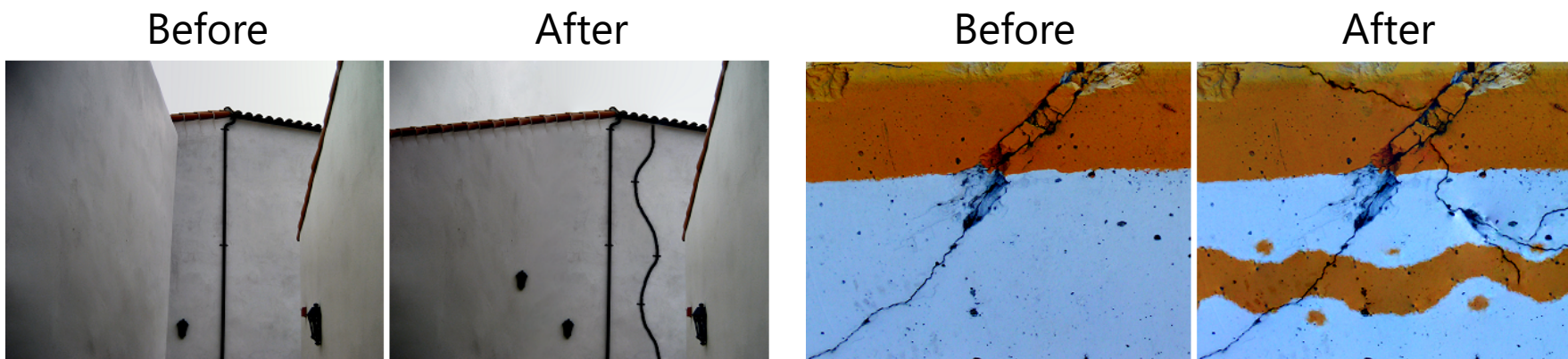
How to give target gradients: mixing

- Copy source's gradient only when its magnitude is larger
 - ➔ smooth part of source won't be copied



How to give target gradient: Edge Brush

- Copy gradients along object silhouette, paste along brush stroke
- Real-time Poisson solver implemented on GPU



Real-Time Gradient-Domain Painting

James McCann Nancy Pollard
Carnegie Mellon University

(With Audio)

<https://www.youtube.com/watch?v=9MGjrsPzFc4>

Real-time gradient-domain painting [McCann SIGGRAPH08]

<http://graphics.cs.cmu.edu/projects/gradient-paint/>

How to give target gradient: modify original



Amplify/suppress within selected region
→ Local Tone Mapping



Set to zero except where detected as edges
→ Stylization

Extra:
Gradient-domain geometry processing

Gradient-domain geometry processing

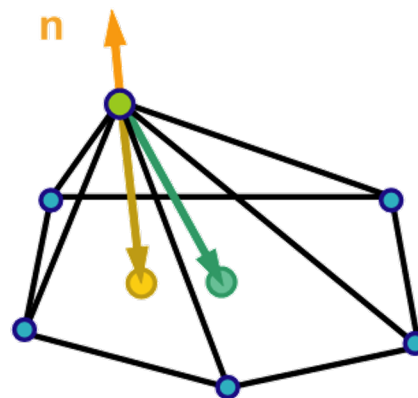
Find $\{ \mathbf{v}_i \}$ that minimize

$$\sum_{(i,j) \in E} w_{ij} \| \mathbf{v}_i - \mathbf{v}_j - \overline{\mathbf{e}_{ij}} \|^2$$

subject to: $\mathbf{v}_c = \mathbf{v}_c^*, c \in I_C$

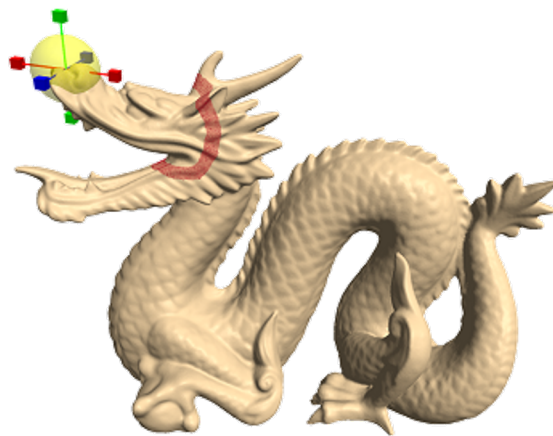
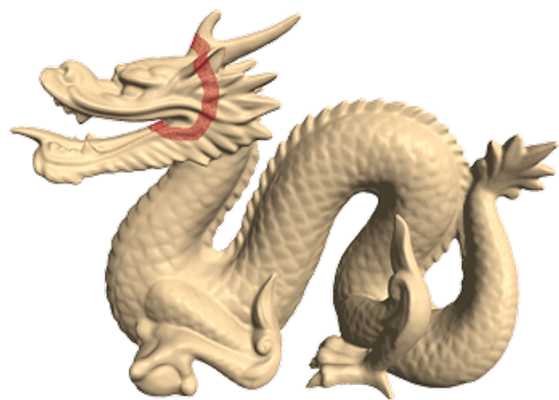
Edge vector of original shape
 \rightarrow target gradient

A few constraints of vertex positions
 \rightarrow boundary condition



Poisson equation

$$\mathbf{L} \mathbf{x} = \delta$$



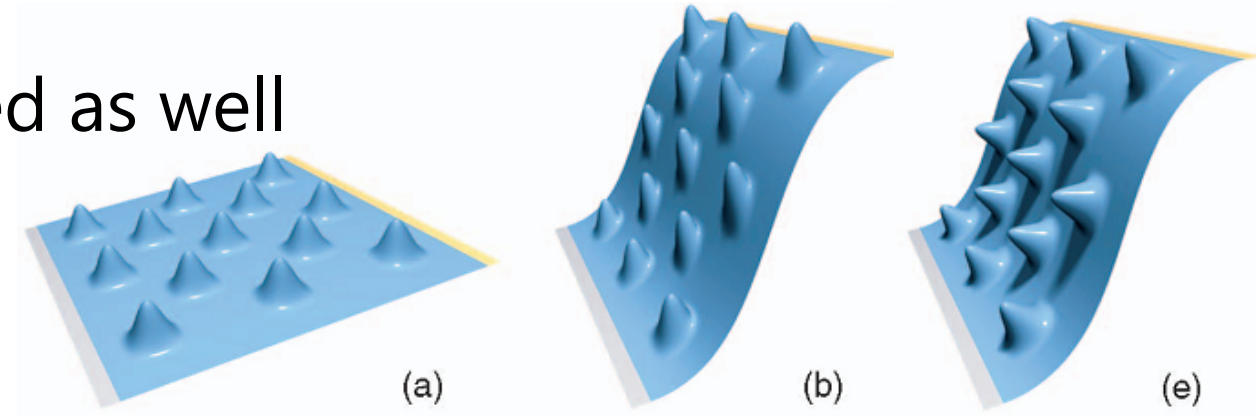
Mesh editing with poisson-based gradient field manipulation [Yu SIGGRAPH04]

Laplacian surface editing [Sorkine SGP04]

Interfaces and algorithms for the creation, modification, and optimization of surface meshes [Nealen PhD07]

Rotation of local region due to large deformation

- Target gradient needs to be rotated as well
 - Non-linear relation
 - Optimal rotation difficult to find



Without rotation

With rotation

- Local-global optimization [Sorkine07]

- **Local step:**

Fix vertex positions,
compute local rotation using SVD

- **Global step:**

Fix local rotations,
compute vertex positions via Poisson equation

As-Rigid-As-Possible Surface Modeling

Olga Sorkine Marc Alexa
TU Berlin



<https://www.youtube.com/watch?v=ltX-qUjkdcc>

GeoBrush: Cloning brush for surface meshes

GeoBrush: Interactive Mesh Geometry Cloning

Kenshi Takayama^{1,2}
Ryan Schmidt³
Karan Singh³
Takeo Igarashi¹
Tamy Boubekeur⁴
Olga Sorkine²

¹The University of Tokyo
²New York University
³University of Toronto
⁴Telecom ParisTech - CNRS LTCI

https://www.youtube.com/watch?v=FPscen_g8E

- Split deformation into two steps:
 1. Rotation of local region
→ Fast & approx. computation using cage-based method
 2. Accurate offset
→ Adapt GPU-based Poisson solver (originally for image processing)

