

UNIVERSITY OF
CAMBRIDGE
COMPUTER LABORATORY



Advanced Graphics & Image Processing

Advanced image processing

Part 1/2 – edge stopping filters

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Edge stopping filters



Original



Edge-aware smoothing



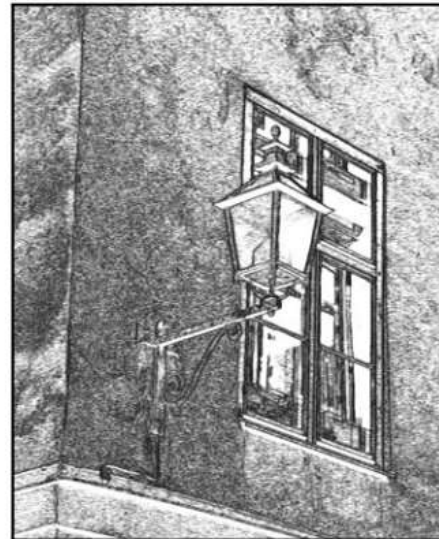
Detail enhancement



Stylization



Recoloring



Pencil drawing



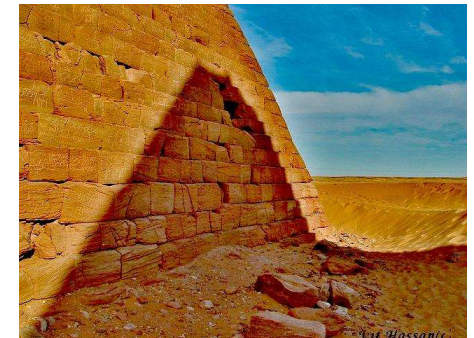
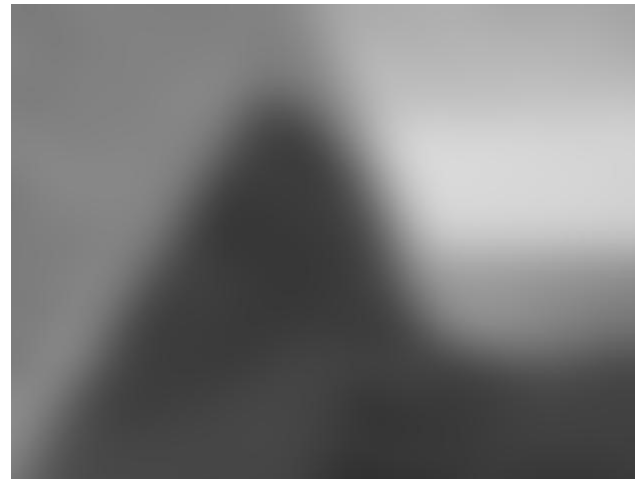
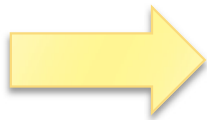
Depth-of-field

Nonlinear filters: Bilateral filter

- ▶ Goal: Smooth out the image without blurring edges



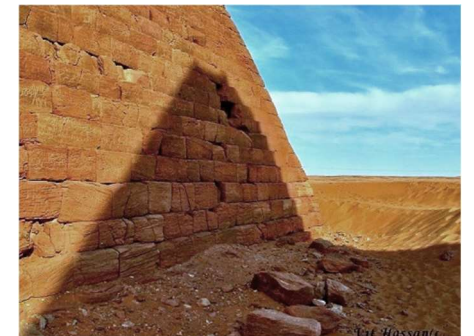
Gaussian
filter



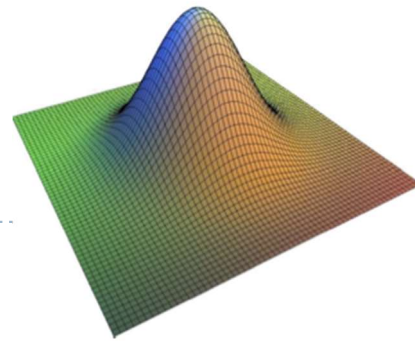
Unsharp masking



Bilateral
filter

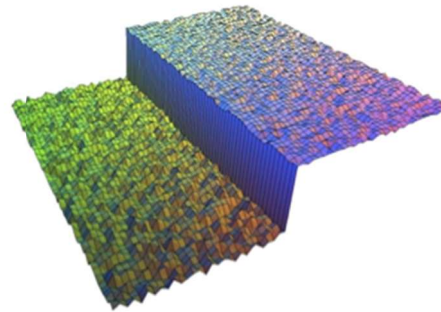


Bilateral filter



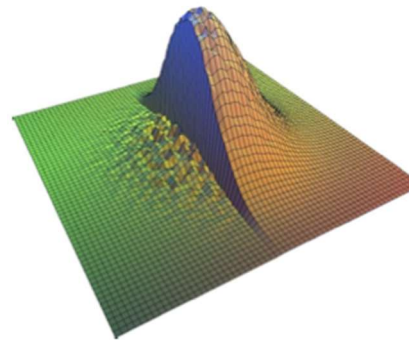
spatial kernel f

■



influence g in the intensity domain for the central pixel

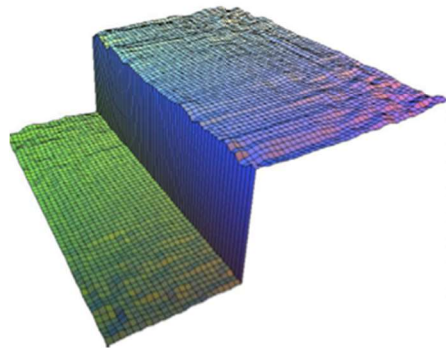
=



weight $f \times g$ for the central pixel

“Kernel” changes from one pixel to another

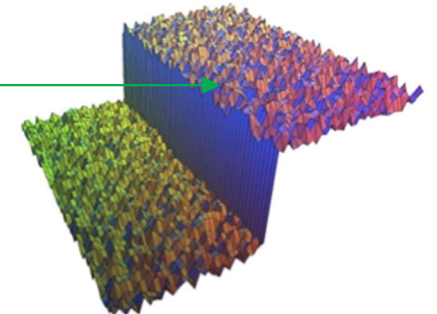
Kernel for this pixel



output

=

*



input

Bilateral filter

Input image

$$y(\mathbf{p}) = \frac{\sum_{\mathbf{q} \in \Omega} x(\mathbf{q}) w(\mathbf{p}, \mathbf{q})}{\sum_{\mathbf{q} \in \Omega} w(\mathbf{p}, \mathbf{q})}$$

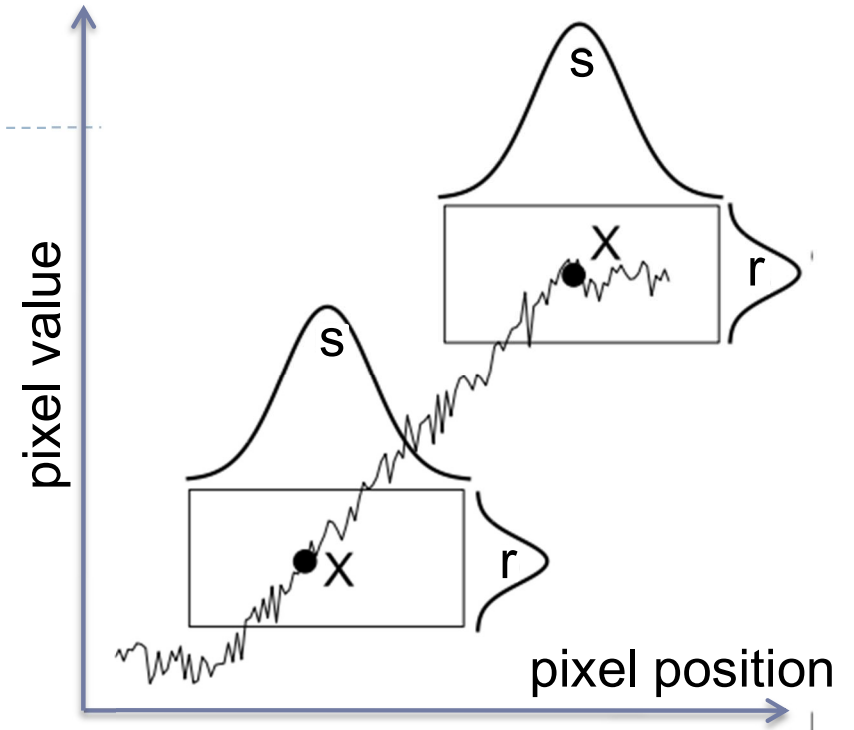
Pixel coordinates
 $\mathbf{p} = (i, j)$

Neighborhood of the pixel \mathbf{p}

$$w(\mathbf{p}, \mathbf{q}) = g_s(\mathbf{p} - \mathbf{q}) g_r(x(\mathbf{p}) - x(\mathbf{q}))$$

distance in the spatial position (x,y) distance (difference) in pixel values

$$g_s(\mathbf{d}) = \exp\left(\frac{-\|\mathbf{d}\|_2}{2\sigma_s^2}\right) \quad g_r(d) = \exp\left(\frac{-d^2}{2\sigma_s^2}\right)$$



How to make the bilateral filter fast?

- ▶ A number of approximations have been proposed
 - ▶ Combination of linear filters [Durand & Dorsey 2002, Yang et al. 2009]
 - ▶ Bilateral grid [Chen et al. 2007]
 - ▶ Permutohedral lattice [Adams et al. 2010]
 - ▶ Domain transform [Gastal & Oliveira 2011]

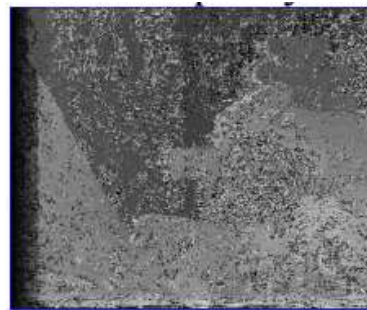
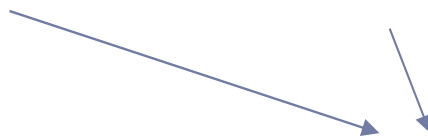
Joint-bilateral filter (a.k.a guided/cross b.f.)

- ▶ The “range” term does not need to operate in the same domain as the filter output

- ▶ Example:



Stereo image pair



Estimated left-to-right disparity

The “spatial”
term operates
on disparities

The “range”
term operates
on the colour
image

Joint bilateral
filter



Filtered disparity

A simplified
algorithm from
[Mueller et al. 2010]

Joint bilateral filter: Flash / no-flash



Flash

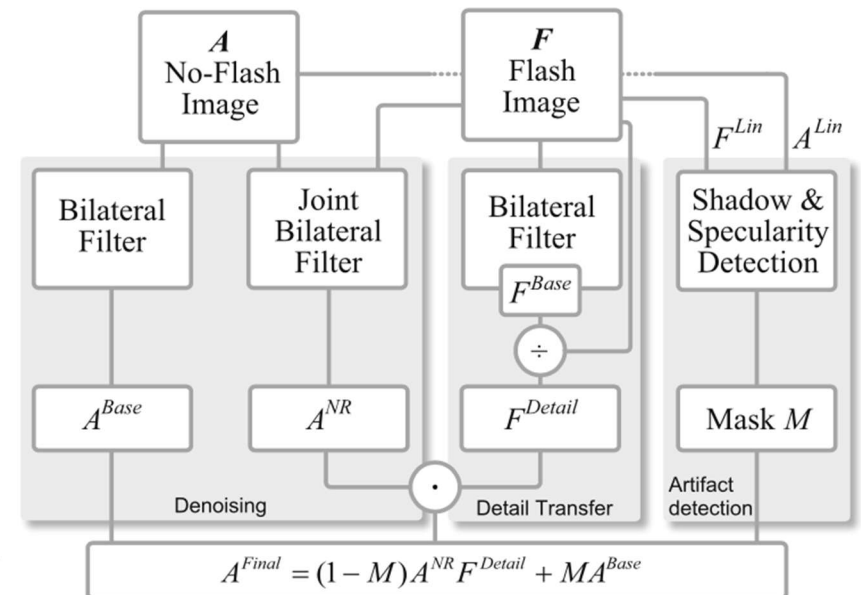


No-flash



Detail transfer with denoising

- ▶ Preserve colour and illumination from the no-flash image
- ▶ Use flash image to remove noise and add details
- ▶ [Petshnigg et al. 2004]



Example of edge preserving filtering

- ▶ Domain Transform for Edge-Aware Image and Video Processing
- ▶ Video:
 - ▶ <https://youtu.be/UlI xh l l QrTY?t=4m l 0s>
 - ▶ From: <http://inf.ufrgs.br/~eslgastal/DomainTransform/>



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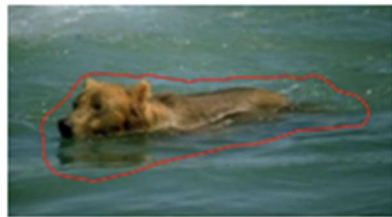
Advanced image processing

Part 1/2 – processing by optimization

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Optimization-based methods



sources/destinations



cloning

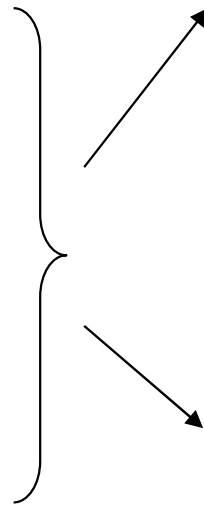


seamless cloning

Poisson image editing [Perez et al. 2003]

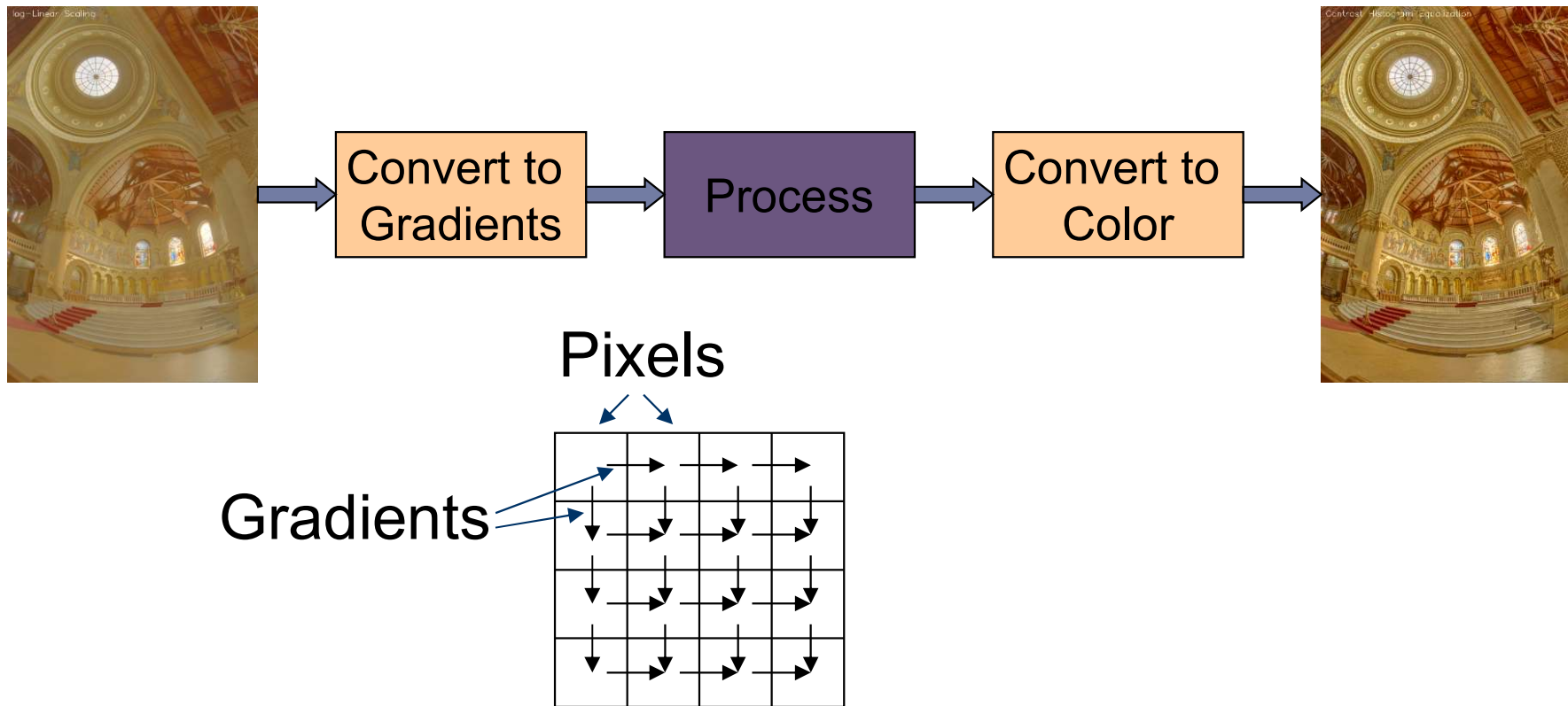
Gradient Domain compositing

- ▶ Compositing [Wang et al. 2004]



Gradient domain methods

- ▶ Operate on pixel gradients instead of pixel values

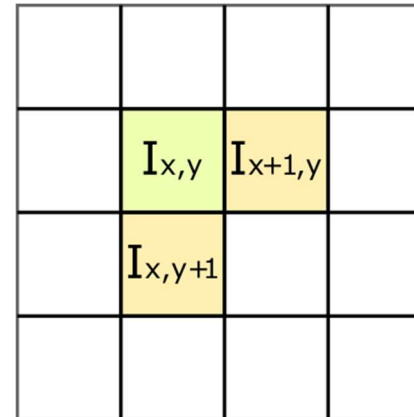


Forward Transformation

- ▶ Forward Transformation

- ▶ Compute gradients as differences between a pixel and its two neighbors

$$\nabla I_{x,y} = \begin{bmatrix} I_{x+1,y} - I_{x,y} \\ I_{x,y+1} - I_{x,y} \end{bmatrix}$$



- ▶ Result: 2D gradient map (2 x more values than the number of pixels)

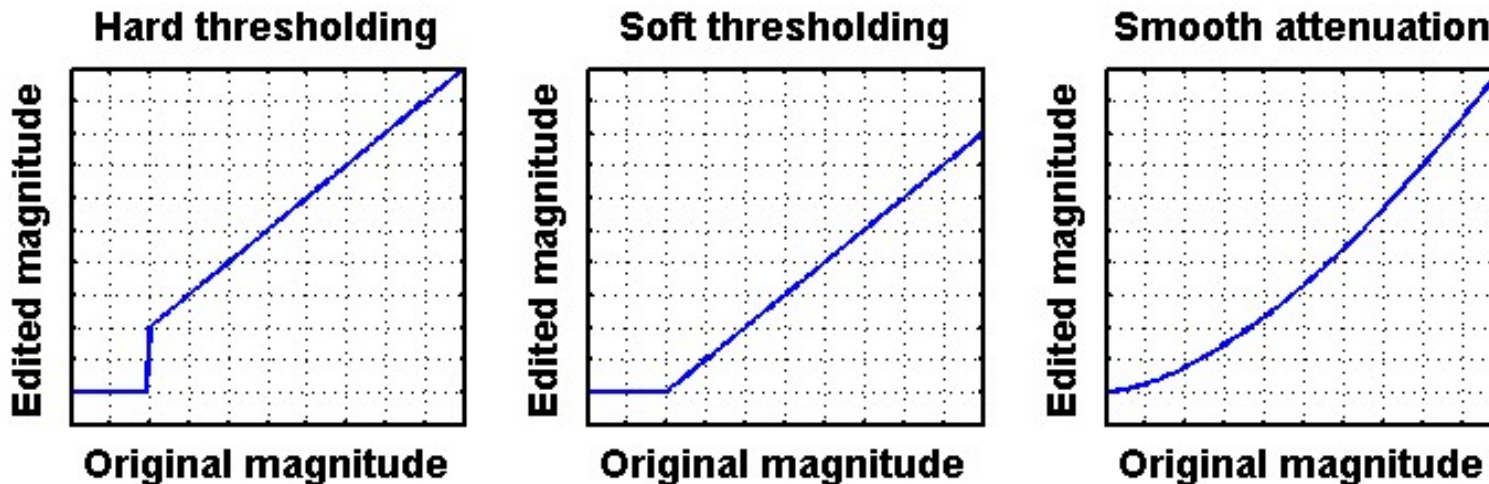
Processing gradient field

- ▶ Usually gradient magnitudes are modified while gradient direction (angle) remains the same

Gradient editing function

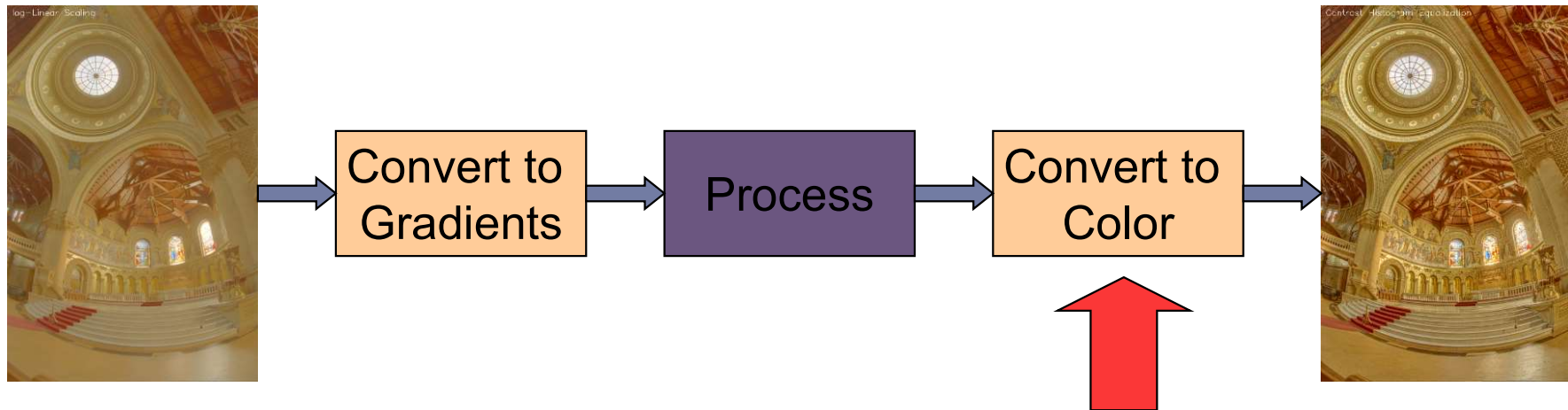
$$G_{x,y} = \nabla I_{x,y} \cdot \frac{f(\|\nabla I_{x,y}\|)}{\|\nabla I_{x,y}\|}$$

- ▶ Examples of gradient editing functions:



Inverse transform: the difficult part

- ▶ There is no straightforward transformation from gradients to luminance



- Instead, a minimization problem is solved:

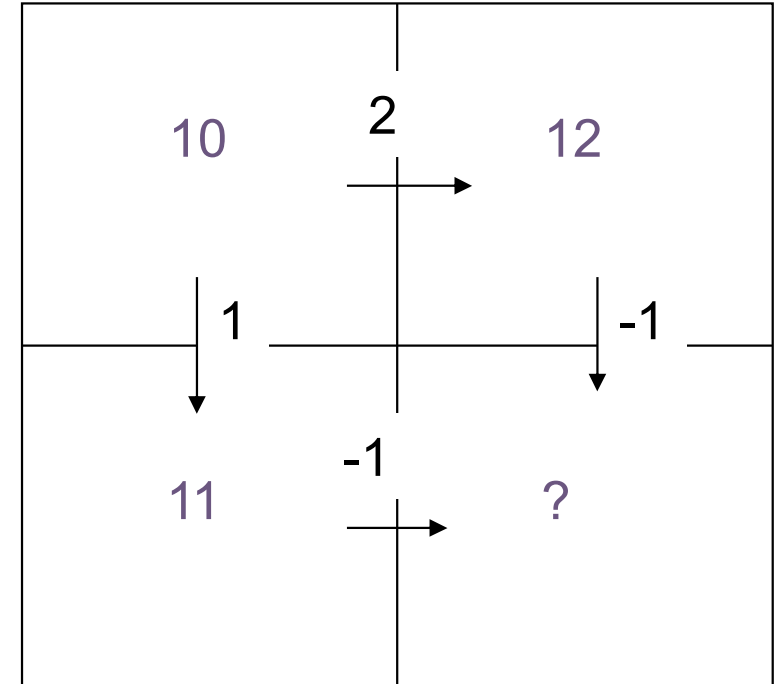
$$\arg \min_I \sum_{x,y} \left[\left(I_{x+1,y} - I_{x,y} - G_{x,y}^{(x)} \right)^2 + \left(I_{x,y+1} - I_{x,y} - G_{x,y}^{(y)} \right)^2 \right]$$

Image Pixels

Desired gradients

Inverse transformation

- ▶ Convert modified gradients to pixel values
 - ▶ Not trivial!
 - ▶ Most gradient fields are inconsistent - do not produce valid images
 - ▶ If no accurate solution is available, take the best possible solution
 - ▶ Analogy: system of springs



Gradient field reconstruction: derivation

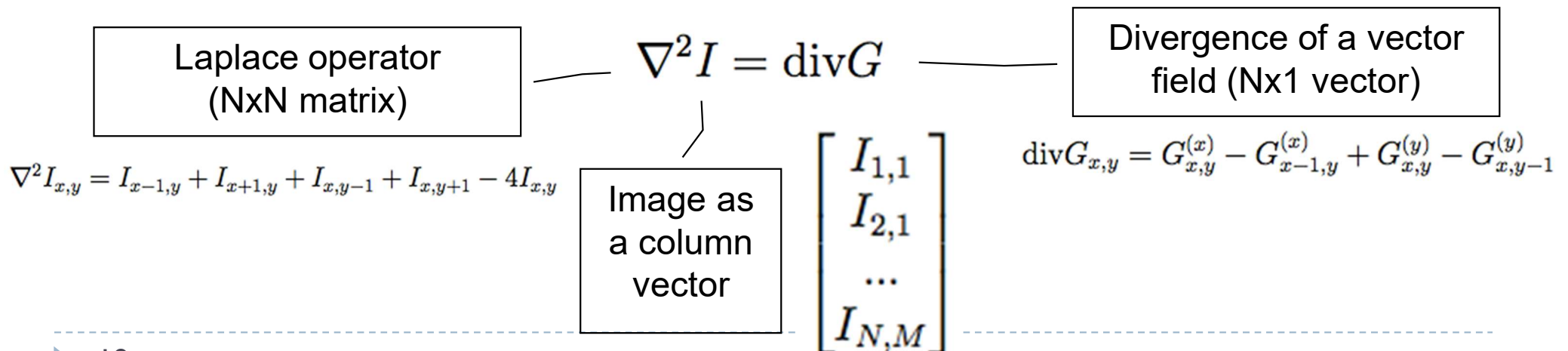
- ▶ The minimization problem is given by:

$$\arg \min_I \sum_{x,y} \left[\left(I_{x+1,y} - I_{x,y} - G_{x,y}^{(x)} \right)^2 + \left(I_{x,y+1} - I_{x,y} - G_{x,y}^{(y)} \right)^2 \right]$$

- ▶ After equating derivatives over pixel values to 0 we get:
 - ▶ Derivation done in the lecture

$$I_{x-1,y} + I_{x+1,y} + I_{x,y-1} + I_{x,y+1} - 4I_{x,y} = G_{x,y}^{(x)} - G_{x-1,y}^{(x)} + G_{x,y}^{(y)} - G_{x,y-1}^{(y)}$$

- ▶ In matrix notation:



Laplace operator for 3x3 image

$$\nabla^2 = \begin{bmatrix} -2 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & -3 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & -2 & 0 & 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & -3 & 1 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 & -4 & 1 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 1 & -3 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 & 0 & -2 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 1 & -3 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & -2 \end{bmatrix}$$

Solving sparse linear systems

- ▶ Just use “\” operator in Matlab / Octave:

- ▶ $x = A \setminus b;$

- ▶ Great “cookbook”:

- ▶ TEUKOLSKY, S.A., FLANNERY, B.P., PRESS, W.H., AND VETTERLING, W.T. 1992.
Numerical recipes in C. Cambridge University Press, Cambridge.

- ▶ Some general methods

- ▶ Cosine-transform – fast but cannot work with weights (next slides) and may suffer from floating point precision errors
 - ▶ Multi-grid – fast, difficult to implement, not very flexible
 - ▶ Conjugate gradient / bi-conjugate gradient – general, memory efficient, iterative but fast converging
 - ▶ Cholesky decomposition – effective when working on sparse matrices

Pinching artefacts

- ▶ A common problem of gradient-based methods is that they may result in “pinching” artefacts (left image)
- ▶ Such artefacts can be avoided by introducing weights to the optimization problem



Weighted gradients

- ▶ The new objective function is:

$$\arg \min_I \sum_{x,y} \left[w_{x,y}^{(x)} (I_{x+1,y} - I_{x,y} - G_{x,y}^{(x)})^2 + w_{x,y}^{(y)} (I_{x,y+1} - I_{x,y} - G_{x,y}^{(y)})^2 \right]$$

- ▶ so that higher weights are assigned to low gradient magnitudes (in the original image).

$$w_{x,y}^{(x)} = w_{x,y}^{(y)} = \frac{1}{\|\nabla I_{x,y}^{(o)}\| + \epsilon}$$

- ▶ The linear system can be derived again
 - ▶ but this is a lot of work and is error-prone

Weighted gradients - matrix notation (1)

- ▶ The objective function:

$$\arg \min_I \sum_{x,y} \left[w_{x,y}^{(x)} (I_{x+1,y} - I_{x,y} - G_{x,y}^{(x)})^2 + w_{x,y}^{(y)} (I_{x,y+1} - I_{x,y} - G_{x,y}^{(y)})^2 \right]$$

- ▶ In the matrix notation (without weights for now):

$$\arg \min_I \left\| \begin{bmatrix} \nabla_x \\ \nabla_y \end{bmatrix} I - \begin{bmatrix} G^{(x)} \\ G^{(y)} \end{bmatrix} \right\|^2$$

- ▶ Gradient operators (for 3x3 pixel image):

$$\nabla_x = \begin{bmatrix} -1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & -1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & -1 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & -1 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & -1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & -1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$\nabla_y = \begin{bmatrix} -1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & -1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & -1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & -1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Weighted gradients - matrix notation (2)

- ▶ The objective function again:
$$\arg \min_I \left\| \begin{bmatrix} \nabla_x \\ \nabla_y \end{bmatrix} I - \begin{bmatrix} G^{(x)} \\ G^{(y)} \end{bmatrix} \right\|^2$$

- ▶ Such over-determined least-square problem can be solved using pseudo-inverse:

$$\begin{bmatrix} \nabla'_x & \nabla'_y \end{bmatrix} \begin{bmatrix} \nabla_x \\ \nabla_y \end{bmatrix} I = \begin{bmatrix} \nabla'_x & \nabla'_y \end{bmatrix} \begin{bmatrix} G^{(x)} \\ G^{(y)} \end{bmatrix}$$

- ▶ Or simply:

$$\left(\nabla'_x \nabla_x + \nabla'_y \nabla_y \right) I = \nabla'_x G^{(x)} + \nabla'_y G^{(y)}$$

- ▶ With weights:

$$\left(\nabla'_x W \nabla_x + \nabla'_y W \nabla_y \right) I = \nabla'_x W G^{(x)} + \nabla'_y W G^{(y)}$$

WLS filter: Edge stopping filter by optimization

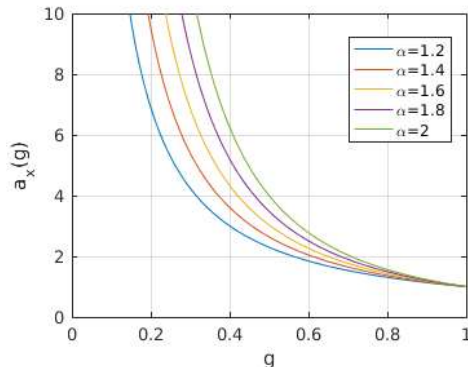
► Weighted-least-squares optimization

Make reconstructed image u possibly close to input g

Smooth out the image by making partial derivatives close to 0

$$\operatorname{argmin}_{\mathbf{u}} \sum_p \left((u_p - g_p)^2 + \lambda \left(a_{x,p}(g) \left(\frac{\partial u}{\partial x} \right)_p^2 + a_{y,p}(g) \left(\frac{\partial u}{\partial y} \right)_p^2 \right) \right)$$

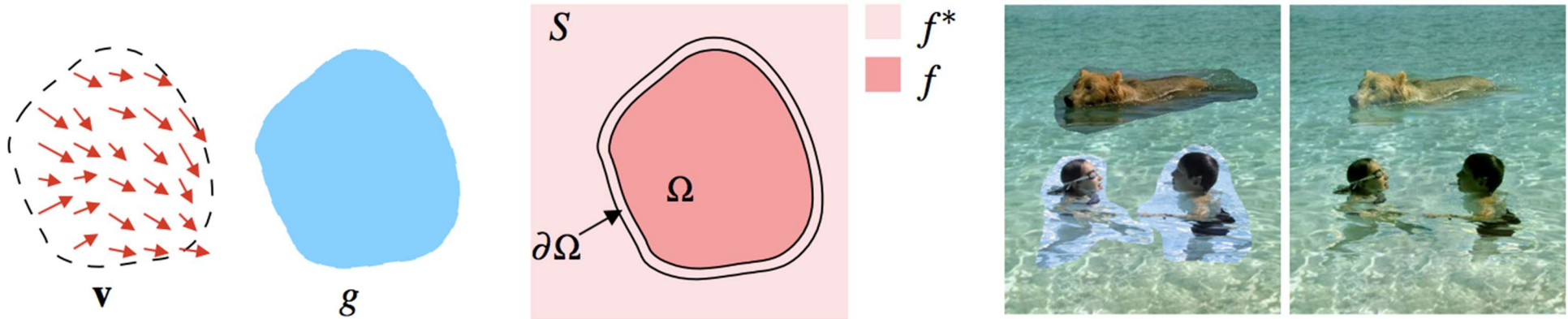
Spatially varying smoothing – less smoothing near the edges



$$a_{x,p}(g) = \frac{1}{\left| \frac{\partial u}{\partial x} (g) \right|^\alpha + \epsilon}$$

- [Farbman, Z., Fattal, R., Lischinski, D., & Szeliski, R. (2008). Edge-preserving decompositions for multi-scale tone and detail manipulation. *ACM SIGGRAPH 2008*, 1–10.]

Poisson image editing



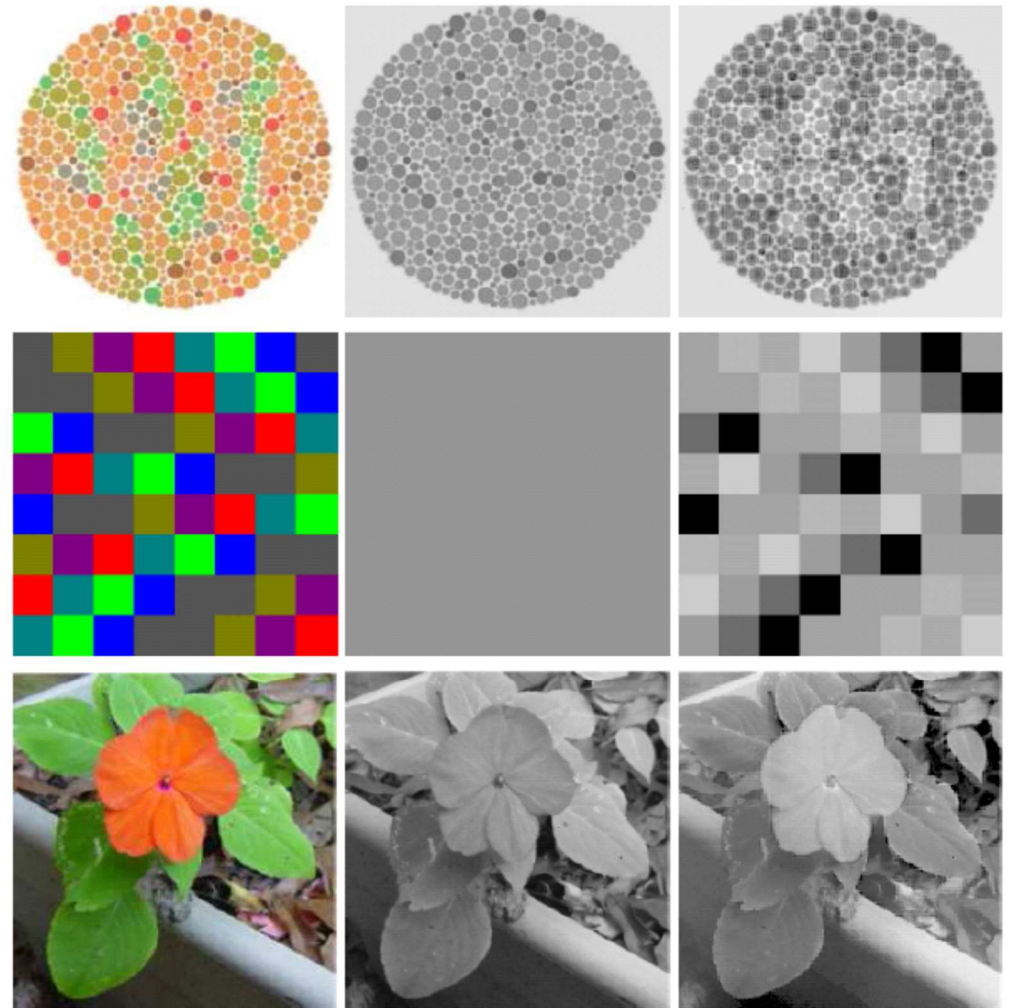
$$\min_f \iint_{\Omega} |\nabla f - \mathbf{v}|^2 \quad \text{subject to:} \quad f|_{\partial\Omega} = f^*|_{\partial\Omega}$$

- ▶ Reconstruct unknown values f given a source guidance gradient field \mathbf{v} and the boundary conditions $f|_{\partial\Omega} = f^*|_{\partial\Omega}$
- ▶ [Pérez, P., Michel Gangnet, & Blake, A. (2003). Poisson Image Editing. *ACM Transactions on Graphics*, 3(22), 313–318. <https://doi.org/10.1145/882262.882269>]



Color 2 Gray

- ▶ Transform color images to gray scale
- ▶ Preserve color saliency
 - ▶ When gradient in luminance close to 0
 - ▶ Replace it with gradient in chrominance
 - ▶ Reconstruct an image from gradients
- ▶ Gooch, A. A., Olsen, S. C., Tumblin, J., & Gooch, B. (2005). Color2Gray. *ACM Transactions on Graphics*, 24(3), 634. <https://doi.org/10.1145/1073204.1073241>



Gradient Domain: applications

- ▶ **More applications:**
 - ▶ Lightness perception (Retinex) [Horn 1974]
 - ▶ Matting [Sun et al. 2004]
 - ▶ Color to gray mapping [Gooch et al. 2005]
 - ▶ Video Editing [Perez et al. 2003, Agarwala et al. 2004]
 - ▶ Photoshop's Healing Brush [Georgiev 2005]

References

- ▶ F. Durand and J. Dorsey, “Fast bilateral filtering for the display of high-dynamic-range images,” *ACM Trans. Graph.*, vol. 21, no. 3, pp. 257–266, Jul. 2002.
- ▶ E. S. L. Gastal and M. M. Oliveira, “Domain transform for edge-aware image and video processing,” *ACM Trans. Graph.*, vol. 30, no. 4, p. 1, Jul. 2011.
- ▶ Patrick Pérez, Michel Gangnet, and Andrew Blake. 2003. Poisson image editing. *ACM Trans. Graph.* 22, 3 (July 2003), 313-318. DOI: <http://dx.doi.org/10.1145/882262.882269>
- ▶ Zeev Farbman, Raanan Fattal, Dani Lischinski, and Richard Szeliski. 2008. Edge-preserving decompositions for multi-scale tone and detail manipulation. *ACM Trans. Graph.* 27, 3, Article 67 (August 2008), 10 pages. DOI: <https://doi.org/10.1145/1360612.1360666>