

Digital Image

(B4M33DZO, Summer 2024)

Lecture 6:

Image Editing

<https://cw.fel.cvut.cz/wiki/courses/b4m33dzo/start>

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How to stitch two similar images?



We can use histogram mapping to reach similar intensity level.

Problem: local changes still remain visible along the seam.

Spatially weighted linear combination of images:

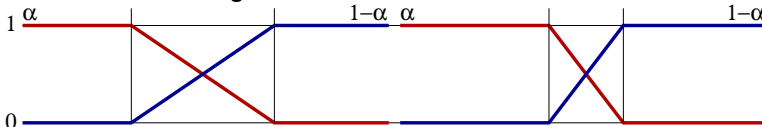
$$\mathbf{I}[x, y] = \alpha \cdot \mathbf{I}_a[x, y] + (1 - \alpha) \cdot \mathbf{I}_b[x, y]$$



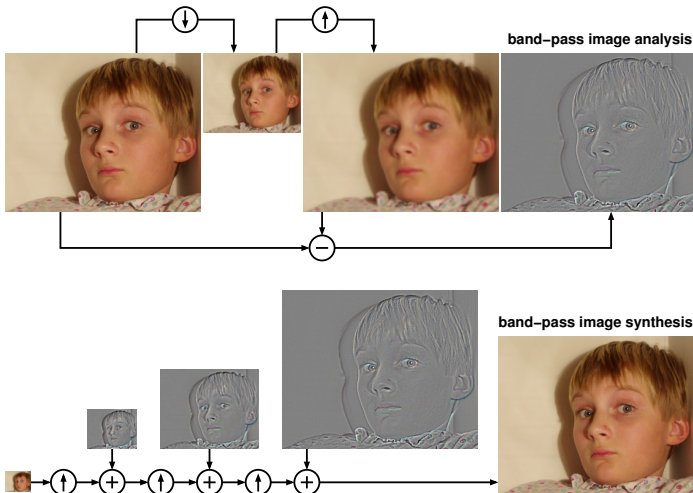
too wide – ghosts



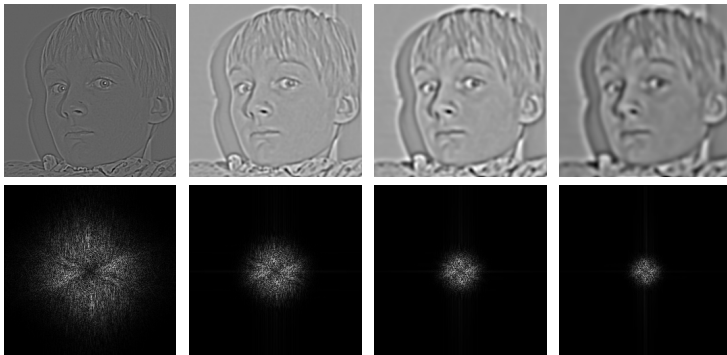
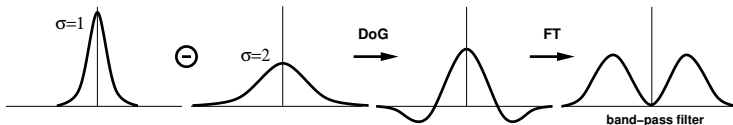
too narrow – seam



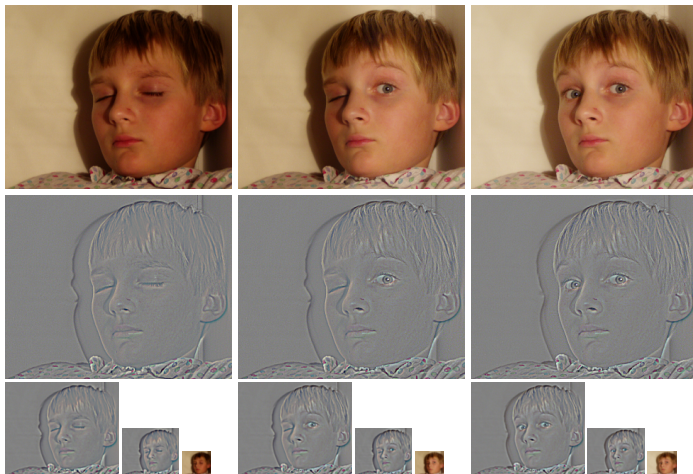
Band-pass image analysis and synthesis using Laplacian pyramid:



Difference of Gaussians $\approx$ Laplacian of Gaussian (band-pass filter):

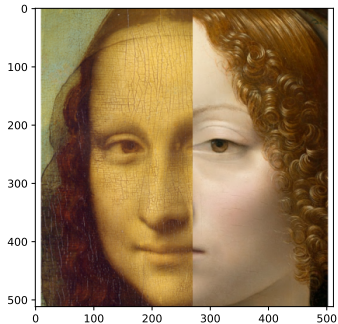


Blend each level of Laplacian pyramid and synthesize the image:

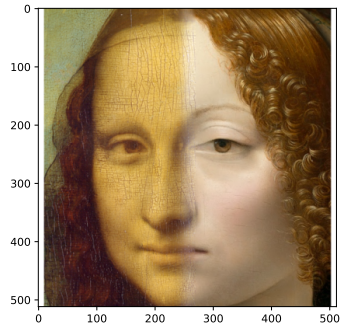


With images from lab task:

concatenation

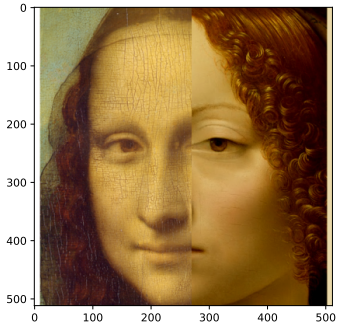


fusion

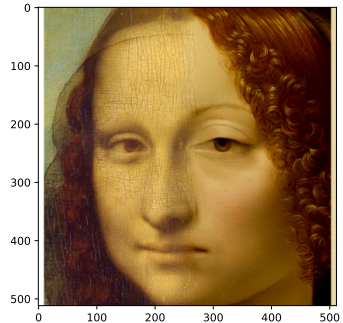


After color adjustment:

concatenation

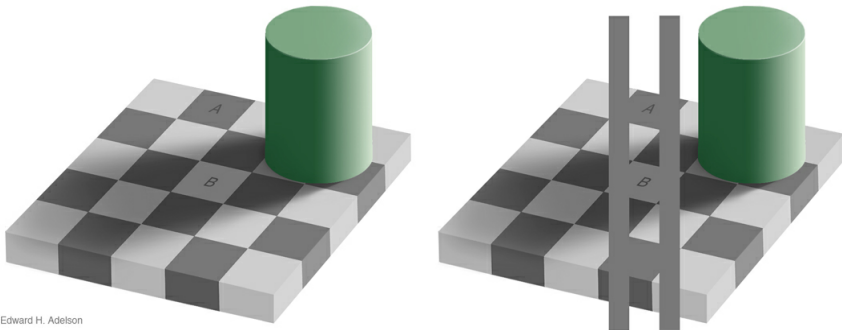


fusion



Human visual system is not very sensitive to absolute intensity.

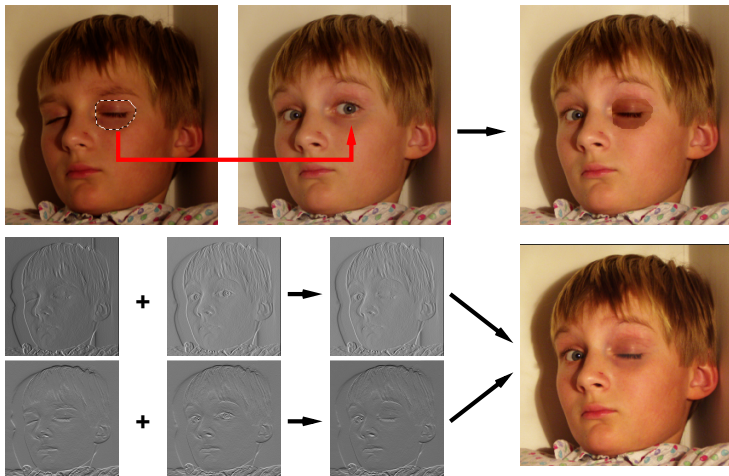
Adelson's checkerboard illusion:



Edward H. Adelson

Local intensity changes (gradients) are much more important.

New approach: modify gradients and then reconstruct intensity.



Problem: only conservative gradient field can be integrated in 2D.

$$\nabla I = G \implies I = \iint G \iff \oint G = 0$$

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$$I^* = \arg \min_I \iint \left(\frac{\partial I}{\partial x} - G_x \right)^2 + \left(\frac{\partial I}{\partial y} - G_y \right)^2$$

We want to minimize:

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Variational Principle (Euler-Lagrange equation):

$$\frac{\partial F}{\partial I} - \frac{d}{dx} \frac{\partial F}{\partial I_x} - \frac{d}{dy} \frac{\partial F}{\partial I_y} = 0 \quad \Rightarrow \quad 2 \left(\frac{\partial^2 I}{\partial x^2} - \frac{\partial G_x}{\partial x} \right) + 2 \left(\frac{\partial^2 I}{\partial y^2} - \frac{\partial G_y}{\partial y} \right) = 0$$

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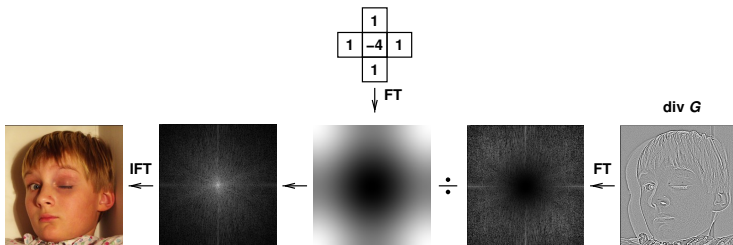
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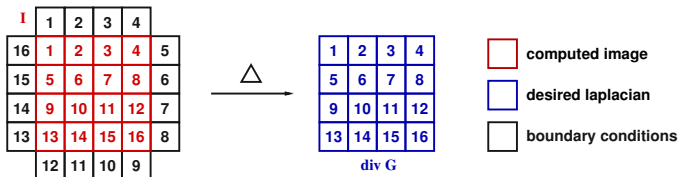
Poisson equation:

$$\frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2} = \Delta I \quad \boxed{\Delta I = \operatorname{div} G} \quad \operatorname{div} G = \frac{\partial G_x}{\partial x} + \frac{\partial G_y}{\partial y}$$

Deconvolution:



Discretization of Poisson equation:



The matrix equation represents the discretized Poisson equation. The matrix is a 16x16 sparse matrix with a 5x5 block structure. The vector on the right is a 16x1 vector of values (1 to 16).

Matrix:

-4	1			1											
1	-4	1			1										
	1	-4	1			1									
		1	-4				1								
1				-4	1			1							
	1				1	-4	1			1					
		1				1	-4	1			1				
			1				1	-4				1			
				1				1	-4				1		

Equation:

1	=	1	-	1	-	16
2	=	2	-	2		
3	=	3	-	3		
4	=	4	-	4	-	5
5	=	5	-	15		
6	=	6				
7	=	7				
8	=	8	-	6		

Large but very sparse system of linear equations:

$$\mathbf{A}_{[N^2 \times N^2]} \cdot \mathbf{I}_{[N^2]} = \mathbf{b}_{[N^2]}$$

A not stored in memory $\Rightarrow$ direct computation

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Gauss-Seidel:

$$\mathbf{I}'[x, y] = \frac{1}{4} (\mathbf{I}[x + 1, y] + \mathbf{I}[x - 1, y] + \mathbf{I}[x, y + 1] + \mathbf{I}[x, y - 1] - \mathbf{b}[x, y])$$

Multi-resolution scheme:

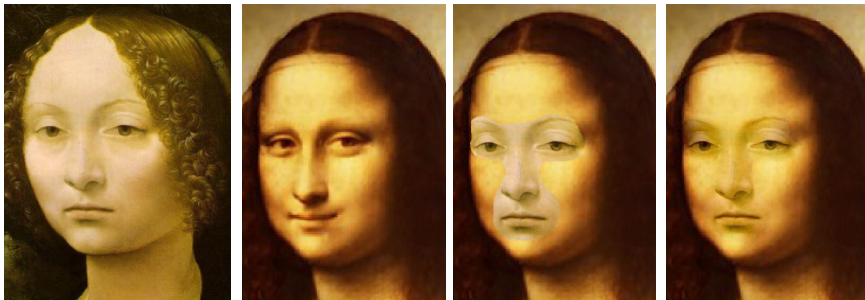


Compute initial solution at lower resolution and refine.

seamless panorama:



seamless cloning:



seamless concealment:



HDR image synthesis:



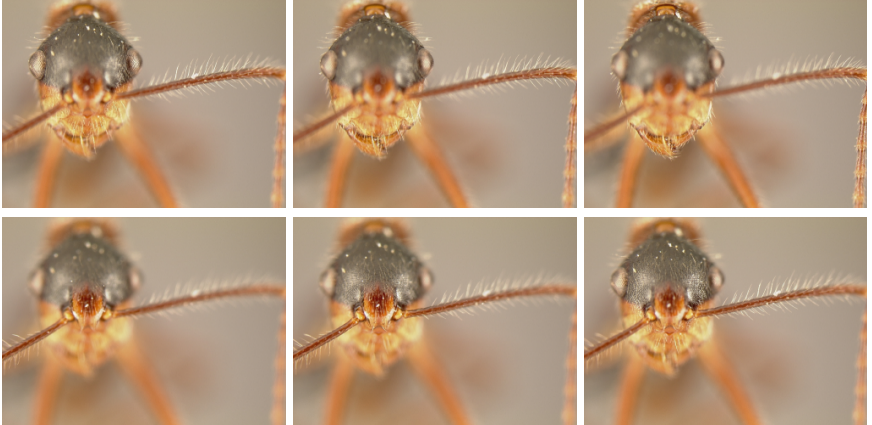
+



HDR image synthesis:



sharp image synthesis:



sharp image synthesis:



group photo synthesis:



group photo synthesis:



group photo synthesis:



group photo synthesis:



group photo synthesis:



group photo synthesis:



color to gray-scale conversion:



intensity



gradients

