

# Digital Image

(B4M33DZO, Winter 2024)

## Lecture 6:

## Image Editing

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

**Daniel Sýkora & Ondřej Drbohlav**

Department of Cybernetics

Faculty of Electrical Engineering

Czech Technical University in Prague

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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:**

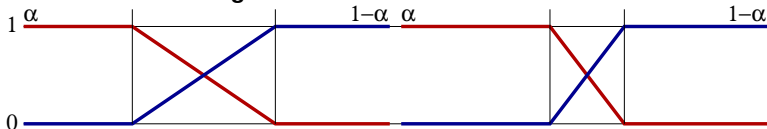
$$I[x, y] = \alpha \cdot I_a[x, y] + (1 - \alpha) \cdot I_b[x, y]$$



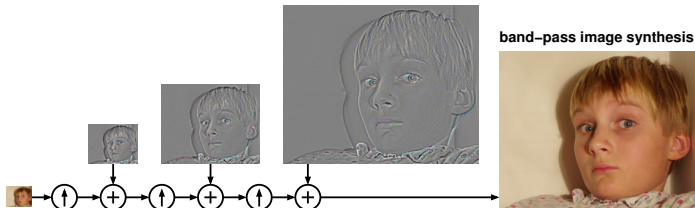
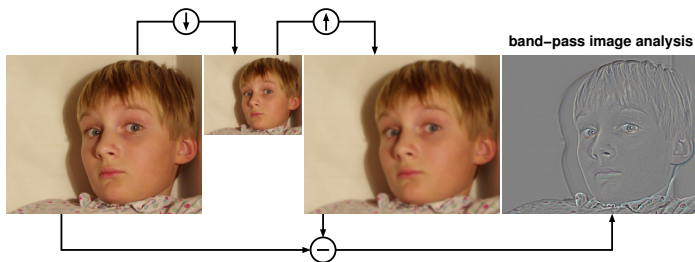
**too wide – ghosts**



**too narrow – seam**

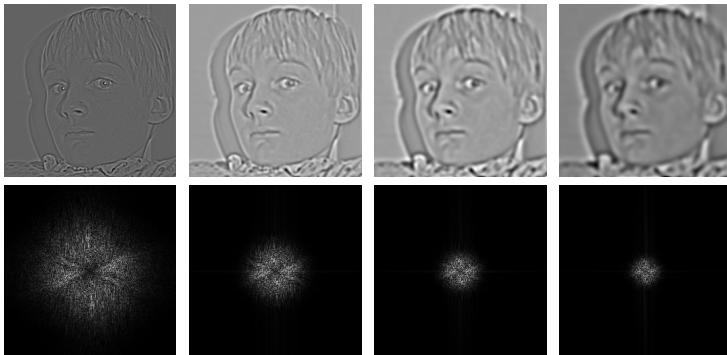
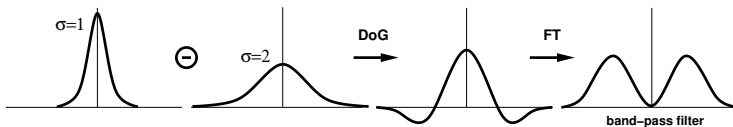


## Band-pass image analysis and synthesis using Laplacian pyramid:

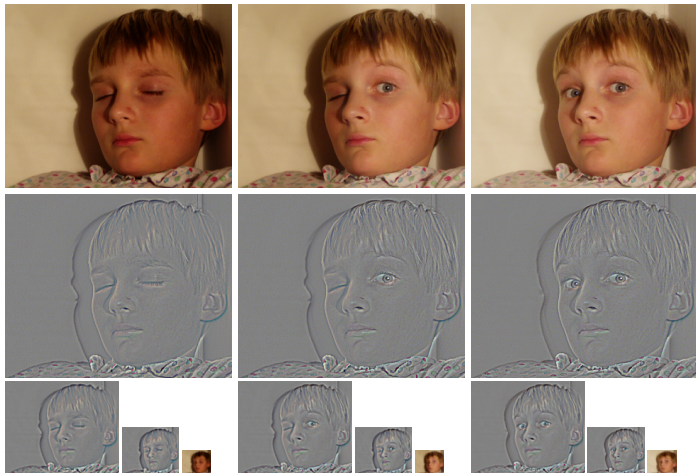




Difference of Gaussians  $\approx$  Laplacian of Gaussian (band-pass filter):

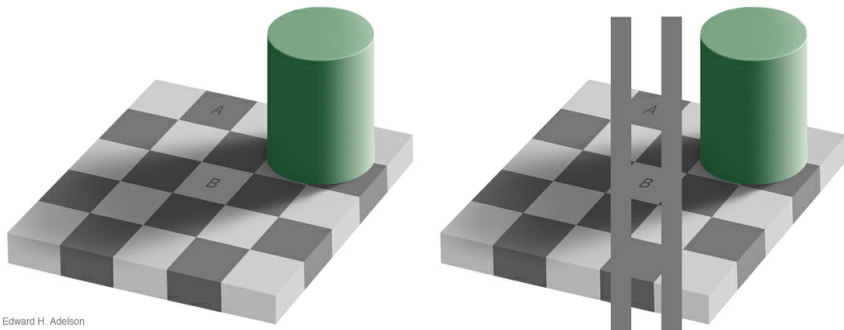


Blend each level of Laplacian pyramid and synthesize the image:



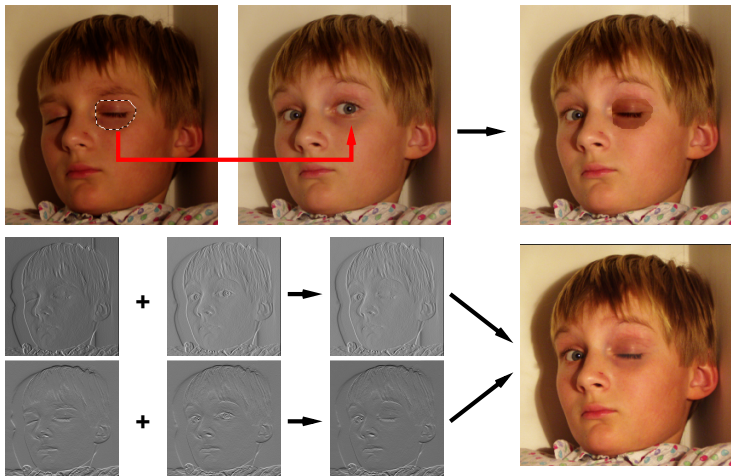
**Human visual system is not very sensitive to absolute intensity.**

**Adelson's checkerboard illusion:**



**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.

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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:

$$\iint \underbrace{\left( \frac{\partial I}{\partial x} - G_x \right)^2 + \left( \frac{\partial I}{\partial y} - G_y \right)^2}_F$$

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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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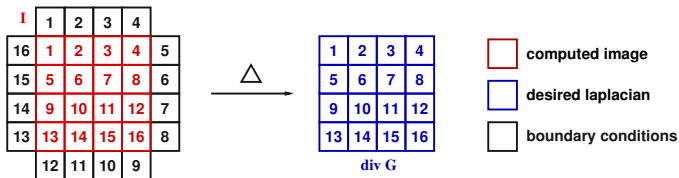
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Poisson equation:

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

## Discretization of Poisson equation:



1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
---	---	---	---	---	---	---	---	---	----	----	----	----	----	----	----

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

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

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**Conjugate gradient:**

$$\mathbf{I}' = \mathbf{I} + \alpha \cdot \mathbf{g} \quad \mathbf{g} = \mathbf{b} - \mathbf{A} \cdot \mathbf{I} \quad \alpha = \frac{\|\mathbf{g}\|}{\mathbf{g}^T \mathbf{A} \mathbf{g}}$$

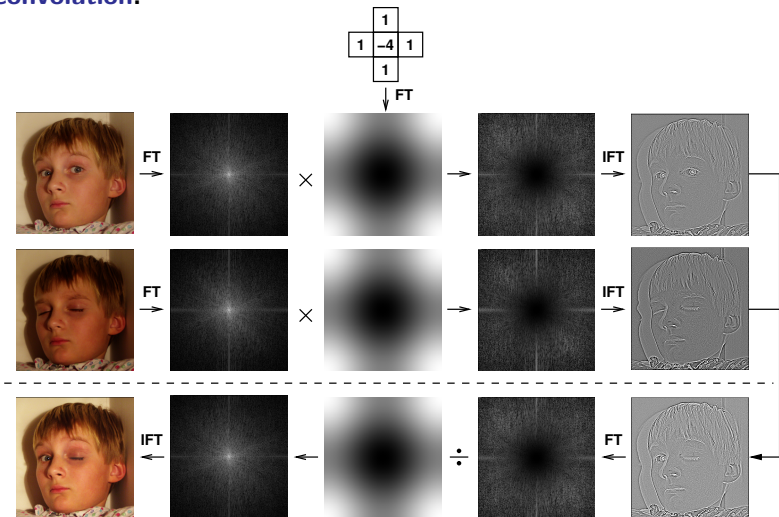
## Multi-resolution scheme:



**Compute initial solution at lower resolution and refine.**



## Deconvolution:



seamless panorama:



seamless cloning:



seamless concealment:



## HDR image synthesis:



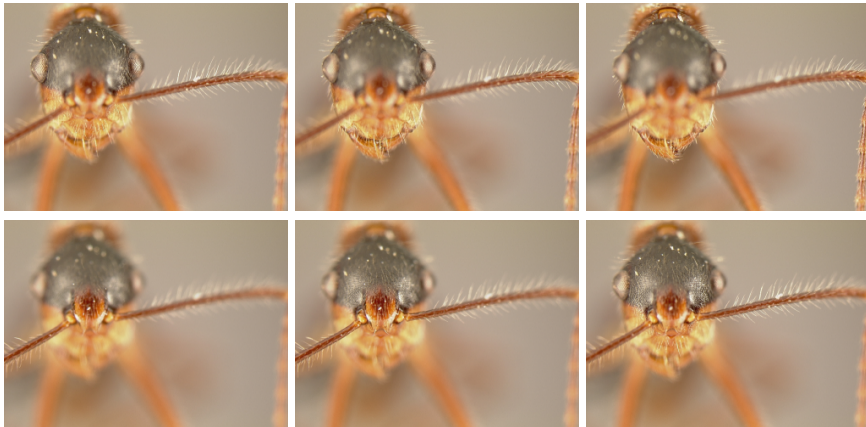
+



## HDR image synthesis:



## sharp image synthesis:



sharp image synthesis:





## group photo synthesis:



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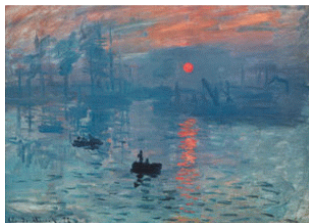
## group photo synthesis:



context enhancement and surrealism:



color to gray-scale conversion:



intensity



gradients





**diffusion curves:**

