

CSCE 448/748 – Computational Photography

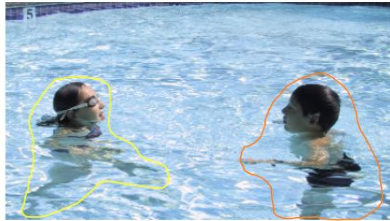
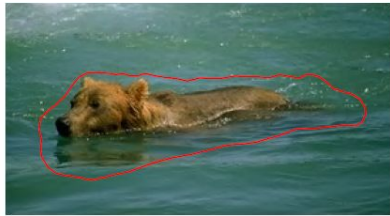
Blending

Nima Kalantari

Many slides from Alexei A. Efros, James Hayes, Rob Fergus

Goal

- **Seamless copy of content from one image to another**



sources/destinations



cloning

Gradient manipulation

□ Observation:

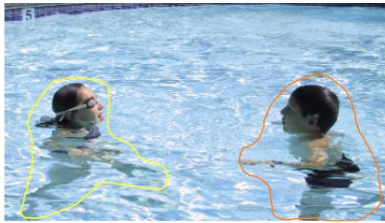
- Human visual system is sensitive to gradient
- Gradient encodes edges and local contrast

□ Idea:

- Do your editing in the gradient domain
- Reconstruct image from gradient

□ Based on Perez et al. "Poisson Image Editing" SIGGRAPH 2003

Goal

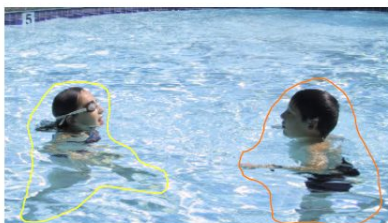


sources/destinations



cloning

Gradient domain cloning



sources/destinations

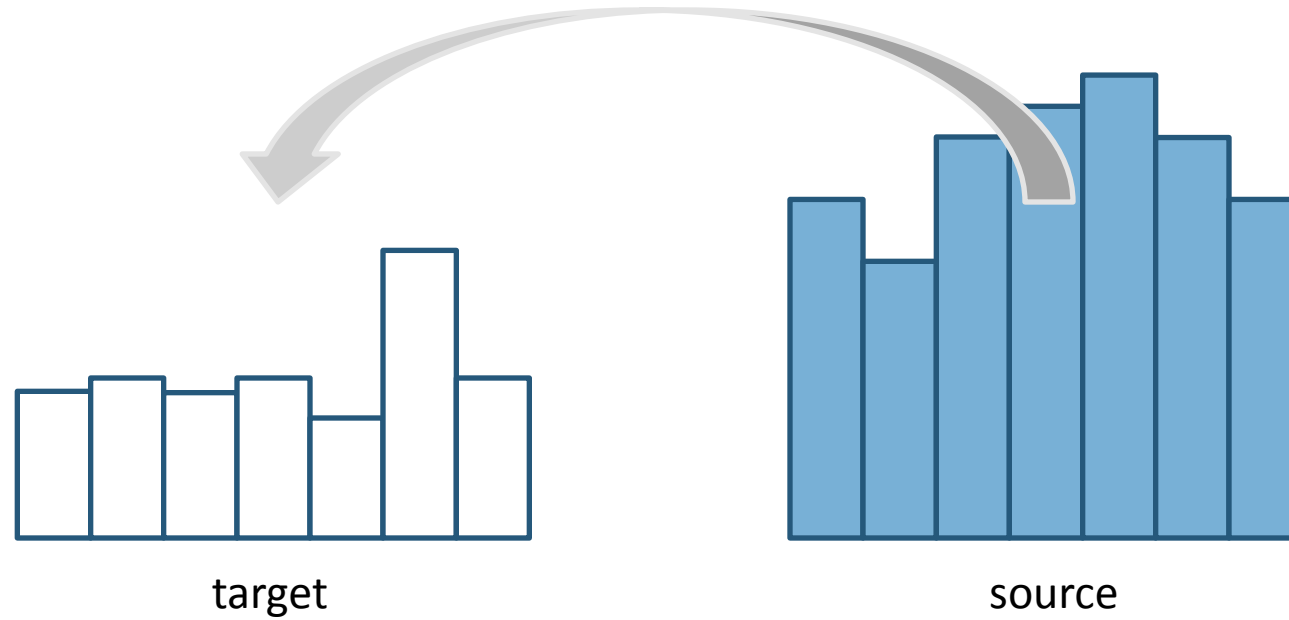


cloning

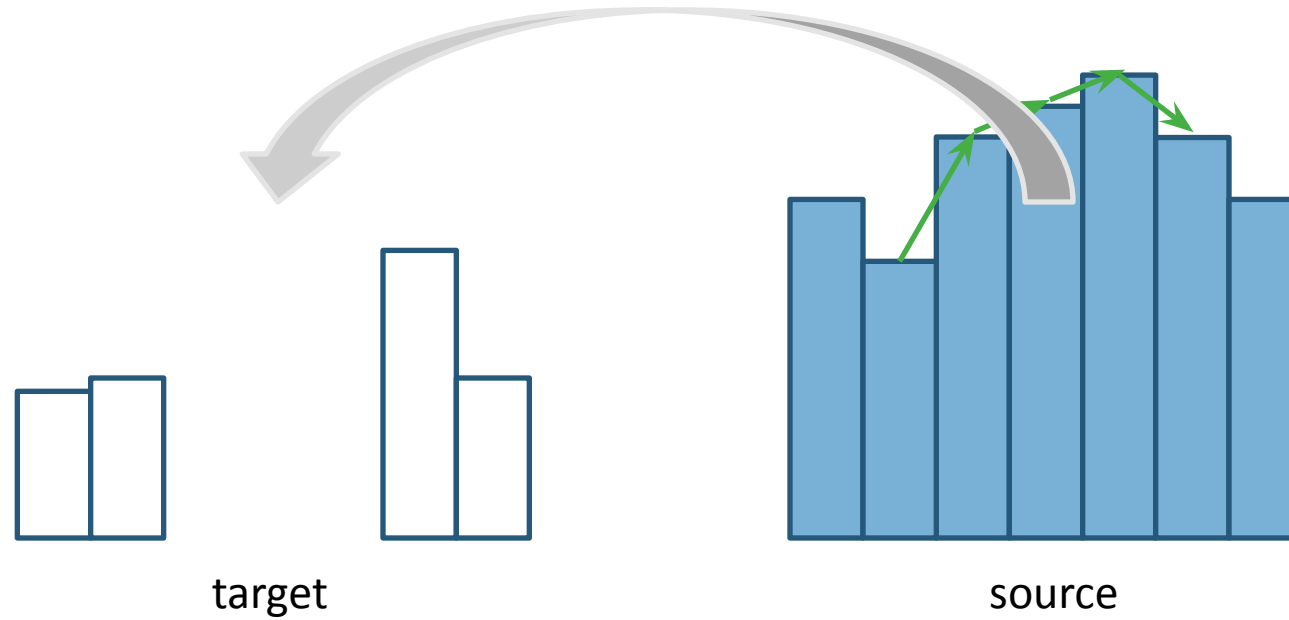


seamless cloning

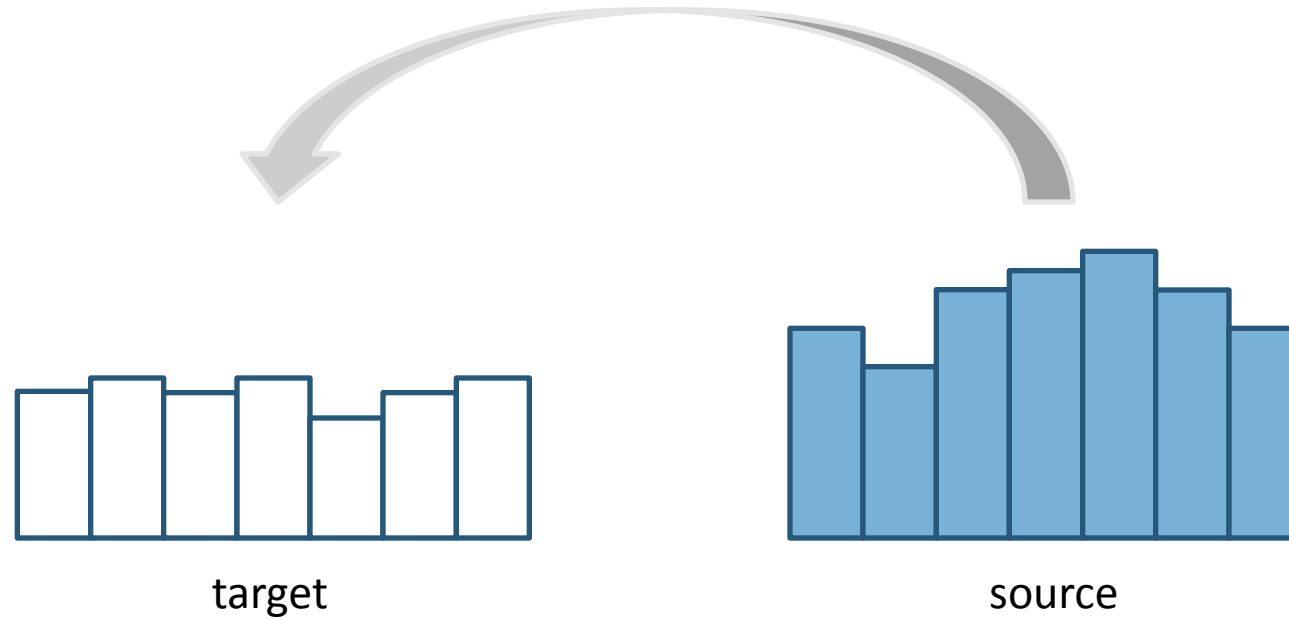
Gradient blending (1D) – Example 1



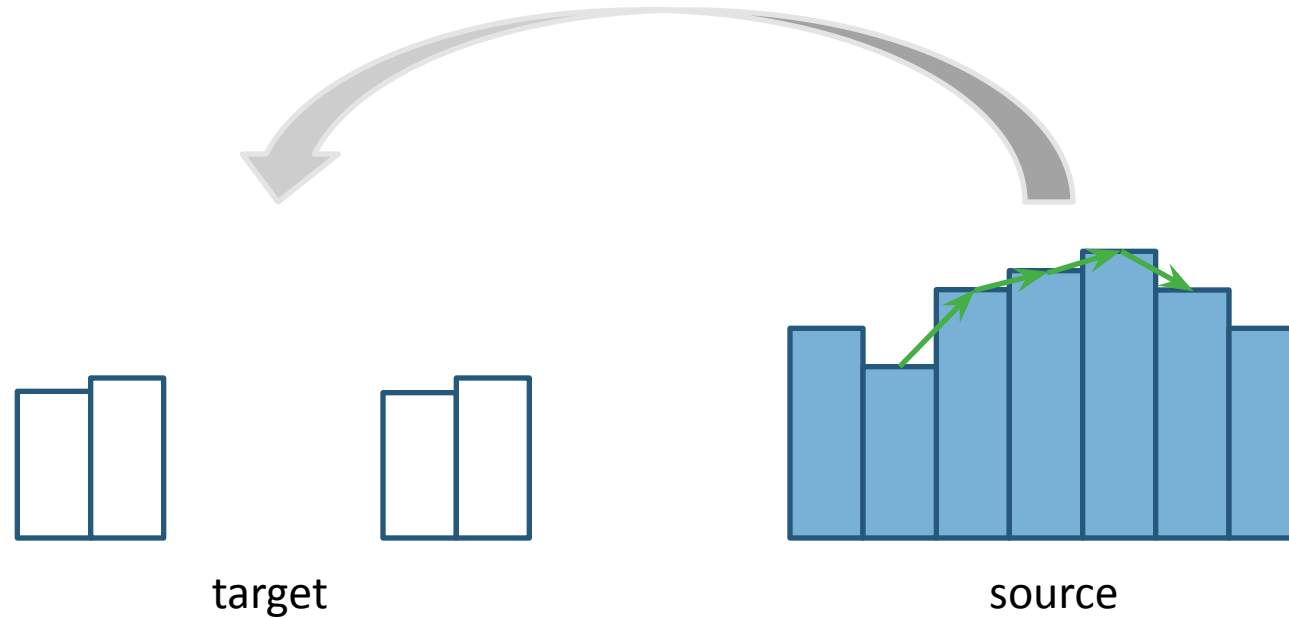
Gradient blending (1D) – Example 1



Gradient blending (1D) – Example 2



Gradient blending (1D) – Example 2

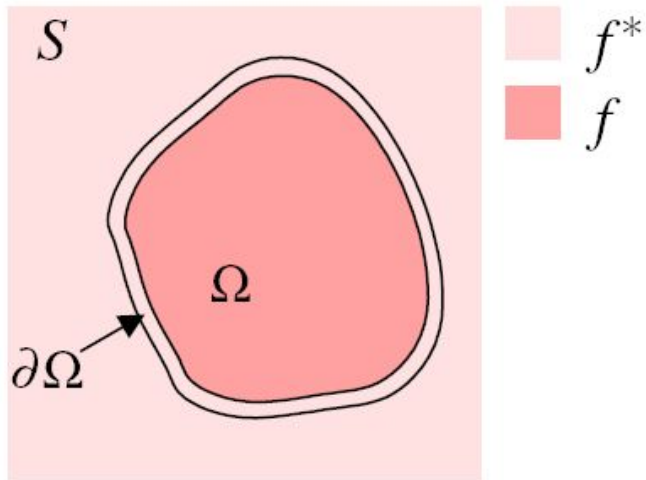


It is impossible to faithfully preserve the gradients

Membrane interpolation

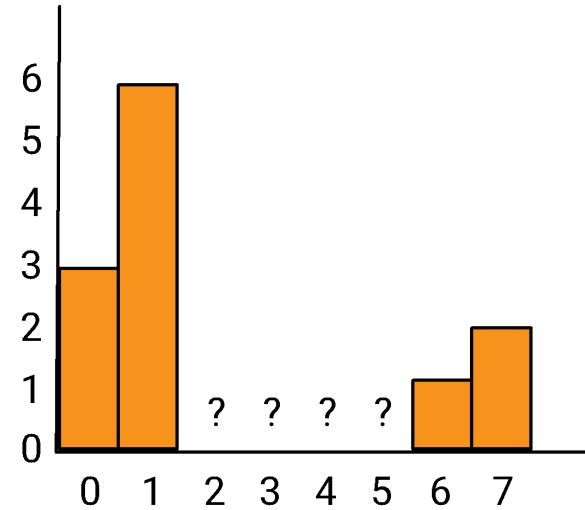
□ Laplace equation (a.k.a. membrane equation)

$$\min_f \iint_{\Omega} |\nabla f|^2 \text{ with } f|_{\partial\Omega} = f^*|_{\partial\Omega}$$



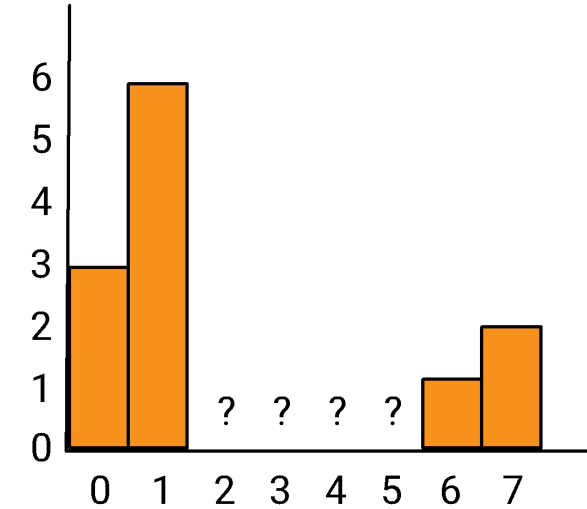
1D example: minimization

- Minimize derivatives to interpolate



1D example: minimization

- Minimize derivatives to interpolate



1	0	0	0	0	0	0	0
0	1	0	0	0	0	0	0
0	-1	2	-1	0	0	0	0
0	0	-1	2	-1	0	0	0
0	0	0	-1	2	-1	0	0
0	0	0	0	-1	2	-1	0
0	0	0	0	0	0	1	0
0	0	0	0	0	0	0	1

 $*$

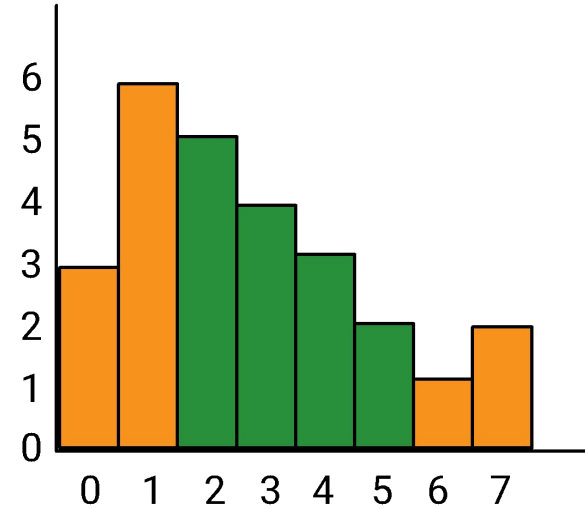
f_0
f_1
f_2
f_3
f_4
f_5
f_6
f_7

 $=$

3
6
0
0
0
0
1
2

1D example

- Minimize derivatives to interpolate
- Pretty much says that second derivative should be zero
- $(-1 \ 2 \ -1)$ is a second derivative filter



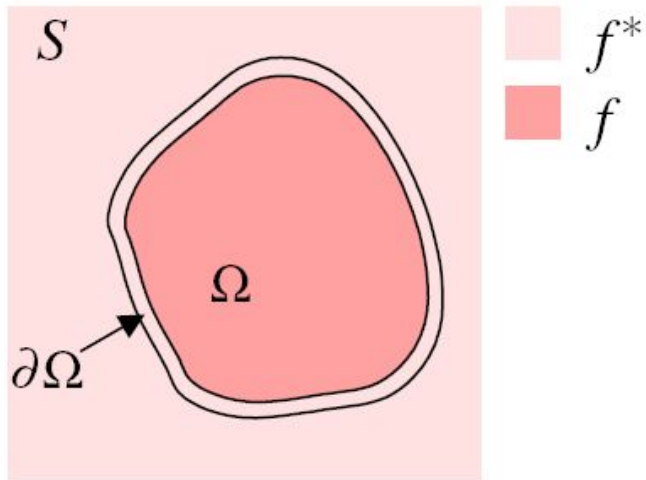
$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & -1 & 2 & -1 & 0 & 0 & 0 & 0 \\ 0 & 0 & -1 & 2 & -1 & 0 & 0 & 0 \\ 0 & 0 & 0 & -1 & 2 & -1 & 0 & 0 \\ 0 & 0 & 0 & 0 & -1 & 2 & -1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} * \begin{bmatrix} f_0 \\ f_1 \\ f_2 \\ f_3 \\ f_4 \\ f_5 \\ f_6 \\ f_7 \end{bmatrix} = \begin{bmatrix} 3 \\ 6 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ 2 \end{bmatrix}$$

$$\begin{bmatrix} f_0 \\ f_1 \\ f_2 \\ f_3 \\ f_4 \\ f_5 \\ f_6 \\ f_7 \end{bmatrix} = \begin{bmatrix} 3 \\ 6 \\ 5 \\ 4 \\ 3 \\ 2 \\ 1 \\ 2 \end{bmatrix}$$

Membrane interpolation

□ Laplace equation (a.k.a. membrane equation)

$$\min_f \iint_{\Omega} |\nabla f|^2 \text{ with } f|_{\partial\Omega} = f^*|_{\partial\Omega}$$

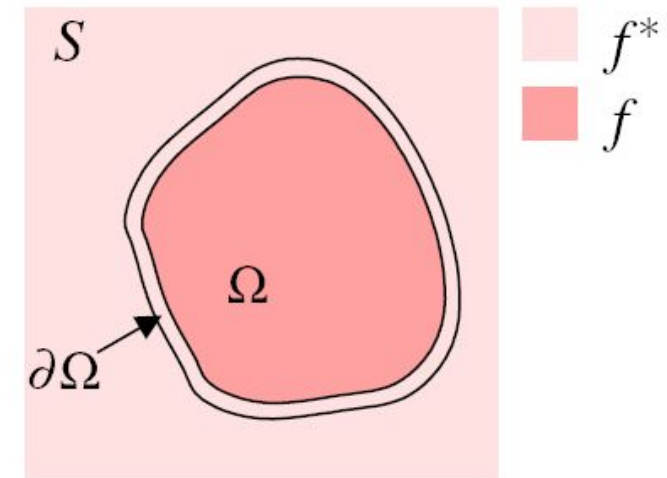
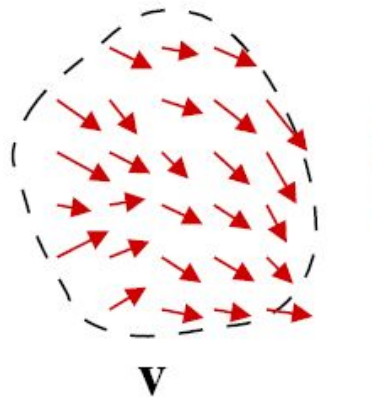


Seamless Poisson cloning

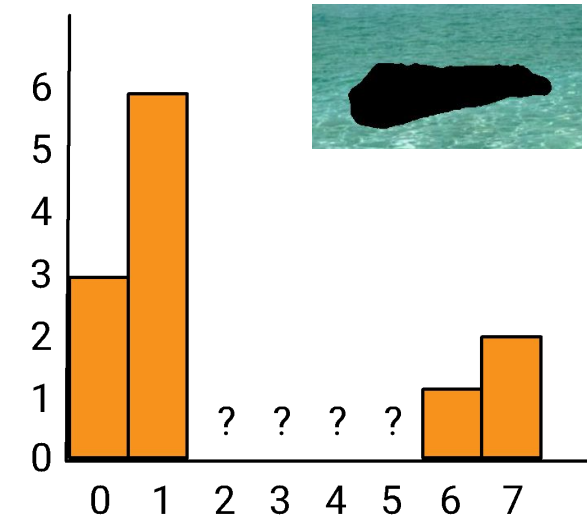
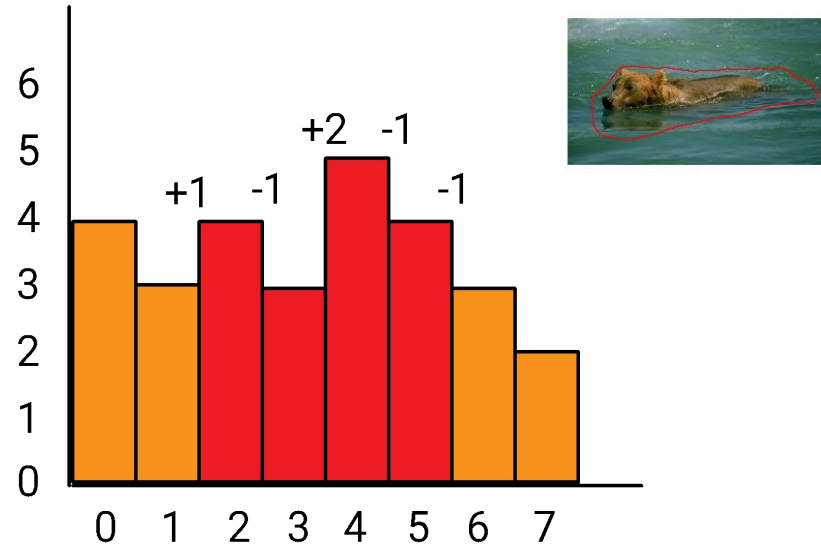
- Given vector field \mathbf{v} (pasted gradient), find the value of f in unknown region that optimize:
- Previously, \mathbf{v} was null

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

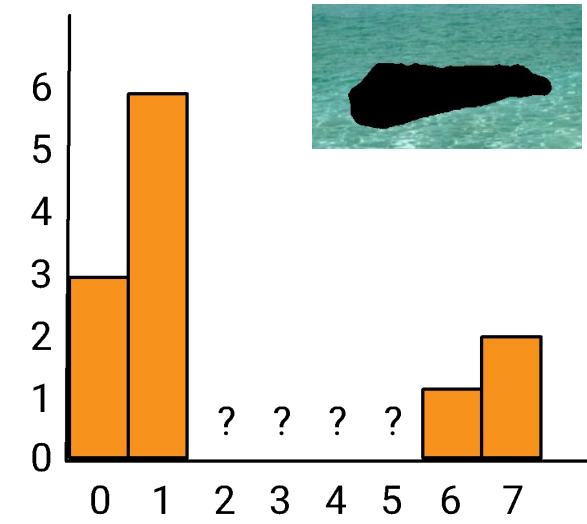
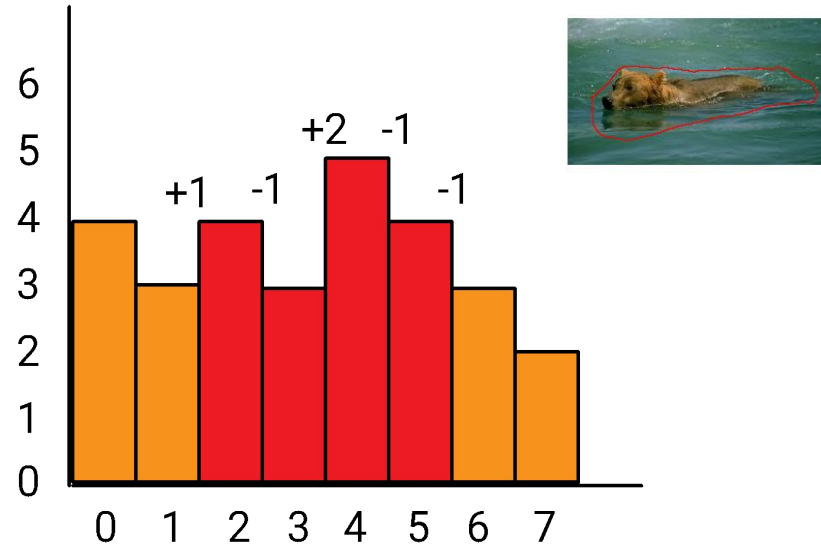
Pasted gradient



Discrete 1D example: minimization



Discrete 1D example: minimization



1	0	0	0	0	0	0	0
0	1	0	0	0	0	0	0
0	-1	2	-1	0	0	0	0
0	0	-1	2	-1	0	0	0
0	0	0	-1	2	-1	0	0
0	0	0	0	-1	2	-1	0
0	0	0	0	0	0	1	0
0	0	0	0	0	0	0	1

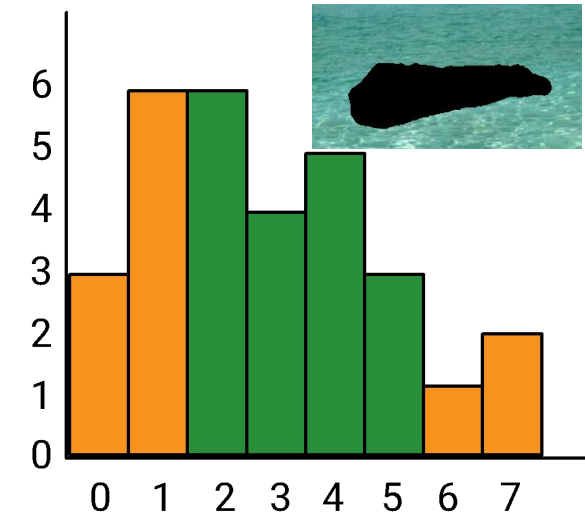
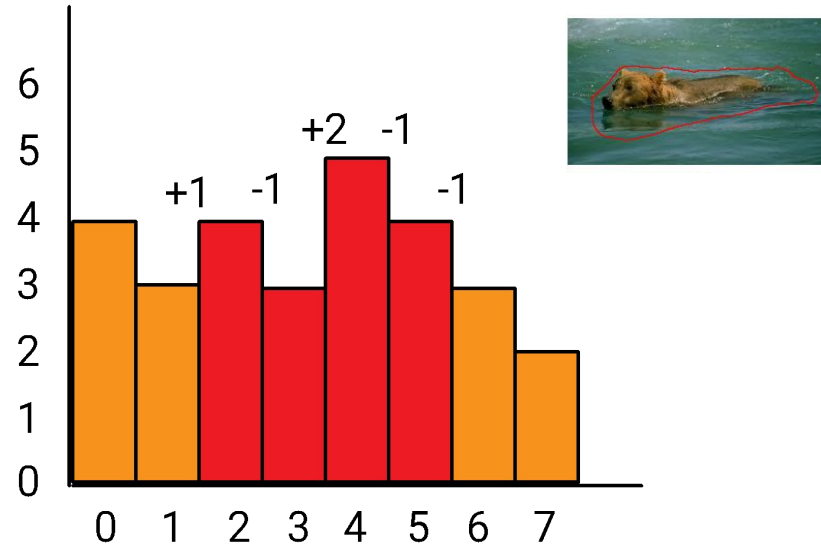
*

f_0
f_1
f_2
f_3
f_4
f_5
f_6
f_7

=

3
6
2
-3
3
0
1
2

Discrete 1D example: minimization



1	0	0	0	0	0	0	0
0	1	0	0	0	0	0	0
0	-1	2	-1	0	0	0	0
0	0	-1	2	-1	0	0	0
0	0	0	-1	2	-1	0	0
0	0	0	0	-1	2	-1	0
0	0	0	0	0	0	1	0
0	0	0	0	0	0	0	1

*

f_0
f_1
f_2
f_3
f_4
f_5
f_6
f_7

=

3
6
2
-3
3
0
1
2

f_0
f_1
f_2
f_3
f_4
f_5
f_6
f_7

=

3
6
6
4
5
3
1
2

Simple 2d example

.2	.5	.2	.2
.7	.7	.7	.7
.9	.9	.8	.9

target, t

.8	.6	.6	.6
.6	.6	.2	.6
.6	.8	.6	.6

source, s

mask



?	?	?	?
?	?	?	?
?	?	?	?

output, x

What properties do we want x to have?

Simple 2d example

.2	.5	.2	.2
.7	.7	.7	.7
.9	.9	.8	.9

target, t

.8	.6	.6	.6
.6	.6	.2	.6
.6	.8	.6	.6

source, s

mask

?	?	?	?
?	?	?	?
?	?	?	?

output, x

- (1) For unmasked pixels, $x_i = t_i$
- (2) For masked pixels, we want the laplacian at x_i to match the laplacian at s_i

Simple 2d example

.2	.5	.2	.2
.7	.7	.7	.7
.9	.9	.8	.9

target, t

.8	.6	.6	.6
.6	.6	.2	.6
.6	.8	.6	.6

source, s

mask

0	-1	0
-1	4	-1
0	-1	0

Laplacian

?	?	?	?
?	?	?	?
?	?	?	?

output, x

1	4	7	10
2	5	8	11
3	6	9	12

Pixel indexing

$$\begin{aligned}
 x_1 &= t_1 \\
 x_2 &= t_2 \\
 x_3 &= t_3 \\
 x_4 &= t_4 \\
 4x_5 - x_4 - x_2 - x_6 - x_8 &= 4s_5 - s_4 - s_2 - s_6 - s_8 \\
 x_6 &= t_6 \\
 x_7 &= t_7 \\
 4x_8 - x_7 - x_5 - x_9 - x_{11} &= 4s_8 - s_7 - s_5 - s_9 - s_{11} \\
 x_9 &= t_9 \\
 x_{10} &= t_{10} \\
 x_{11} &= t_{11} \\
 x_{12} &= t_{12}
 \end{aligned}$$

Simple 2d example

.2	.5	.2	.2
.7	.7	.7	.7
.9	.9	.8	.9

target, t

.8	.6	.6	.6
.6	.6	.2	.6
.6	.8	.6	.6

source, s

mask

0	-1	0
-1	4	-1
0	-1	0

Laplacian

?	?	?	?
?	?	?	?
?	?	?	?

output, x

1	4	7	10
2	5	8	11
3	6	9	12

Pixel indexing

$$x_1 = 0.2$$

$$x_2 = 0.7$$

$$x_3 = 0.9$$

$$x_4 = 0.5$$

$$4x_5 - x_4 - x_2 - x_6 - x_8 = 0.2$$

$$x_6 = 0.9$$

$$x_7 = 0.2$$

$$4x_8 - x_7 - x_5 - x_9 - x_{11} = -1.6$$

$$x_9 = 0.8$$

$$x_{10} = 0.2$$

$$x_{11} = 0.7$$

$$x_{12} = 0.9$$

Simple 2d example

.2	.5	.2	.2
.7	.7	.7	.7
.9	.9	.8	.9

target, t

.8	.6	.6	.6
.6	.6	.2	.6
.6	.8	.6	.6

source, s

mask

0	-1	0
-1	4	-1
0	-1	0

Laplacian

?	?	?	?
?	?	?	?
?	?	?	?

output, x

1	4	7	10
2	5	8	11
3	6	9	12

Pixel indexing

$$x_1 = 0.2$$

$$x_2 = 0.7$$

$$x_3 = 0.9$$

$$x_4 = 0.5$$

$$4x_5 - x_4 - x_2 - x_6 - x_8 = 0.2$$

$$x_6 = 0.9$$

$$x_7 = 0.2$$

$$4x_8 - x_7 - x_5 - x_9 - x_{11} = -1.6$$

$$x_9 = 0.8$$

$$x_{10} = 0.2$$

$$x_{11} = 0.7$$

$$x_{12} = 0.9$$

In this simple case, we could solve for everything by hand.

$$4x_5 - 0.5 - 0.7 - 0.9 - x_8 = 0.2$$

$$4x_8 - 0.2 - x_5 - 0.8 - 0.7 = -1.6$$

$$4x_5 - x_8 = 2.3$$

$$4x_8 - x_5 = 0.1$$

$$x_5 = 0.62$$

$$x_8 = 0.18$$

Simple 2d example

.2	.5	.2	.2
.7	.7	.7	.7
.9	.9	.8	.9

target, t

.8	.6	.6	.6
.6	.6	.2	.6
.6	.8	.6	.6

source, s

mask

0	-1	0
-1	4	-1
0	-1	0

Laplacian

?	?	?	?
?	?	?	?
?	?	?	?

output, x

1	4	7	10
2	5	8	11
3	6	9	12

Pixel indexing

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

A

*

=

?
?
?
?
?
?
?
?
?
?
?

x

.2
.7
.9
.5
.2
.9
.2
-1.6
.8
.2
.7
.9

b

Simple 2d example

.2	.5	.2	.2
.7	.7	.7	.7
.9	.9	.8	.9

target, **t**

.8	.6	.6	.6
.6	.6	.2	.6
.6	.8	.6	.6

source, **s**

mask

0	-1	0
-1	4	-1
0	-1	0

Laplacian

?	?	?	?
?	?	?	?
?	?	?	?

output, **x**

1	4	7	10
2	5	8	11
3	6	9	12

Pixel indexing

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

A

$$\mathbf{A} * \mathbf{x} = \mathbf{b}$$

$$\mathbf{A}^{-1} \mathbf{A} * \mathbf{x} = \mathbf{A}^{-1} \mathbf{b}$$

$$\mathbf{x} = \mathbf{A}^{-1} \mathbf{b}$$

*

=

?
?
?
?
?
?
?
?
?
?

x

.2
.7
.9
.5
.2
.9
.2
-1.6
.8
.2
.7
.9

b

Simple 2d example

.2	.5	.2	.2
.7	.7	.7	.7
.9	.9	.8	.9

target, t

.8	.6	.6	.6
.6	.6	.2	.6
.6	.8	.6	.6

source, s

mask

0	-1	0
-1	4	-1
0	-1	0

Laplacian

?	?	?	?
?	?	?	?
?	?	?	?

output, x

1	4	7	10
2	5	8	11
3	6	9	12

Pixel indexing

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

A

*

=

.2
.7
.9
.5
.62
.9
.2
.18
.8
.2
.7
.9

x

.2
.7
.9
.5
.2
-1.6
.9
.8
.2
.7
.9

b

Simple 2d example

.2	.5	.2	.2
.7	.7	.7	.7
.9	.9	.8	.9

target, t

.8	.6	.6	.6
.6	.6	.2	.6
.6	.8	.6	.6

source, s

mask

0	-1	0
-1	4	-1
0	-1	0

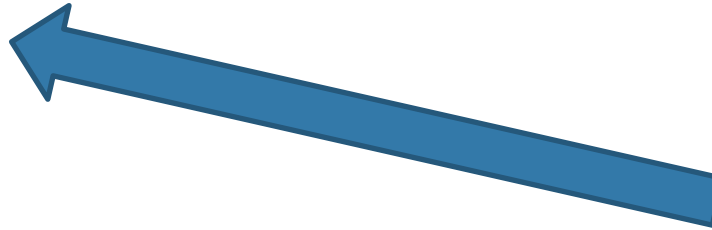
Laplacian

.2	.5	.2	.2
.7	.62	.18	.7
.9	.9	.8	.9

output, x

1	4	7	10
2	5	8	11
3	6	9	12

Pixel indexing



.2
.7
.9
.5
.62
.9
.2
.18
.8
.2
.7
.9

x

Example



target



source



mask



no blending



gradient domain blending

What's the difference?



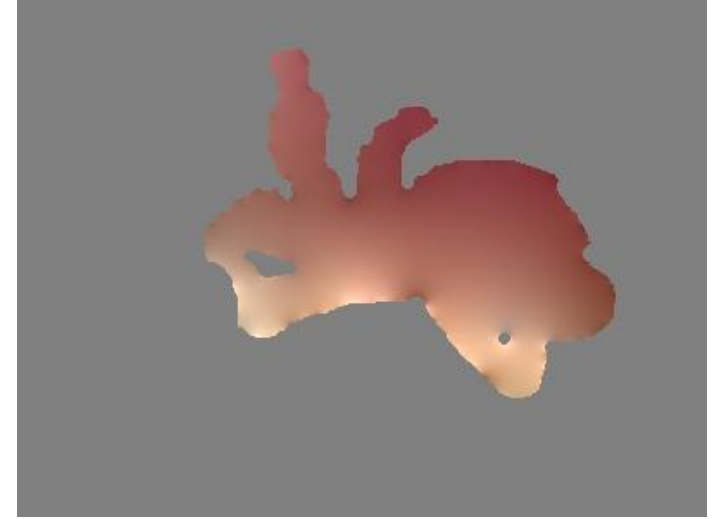
gradient domain blending

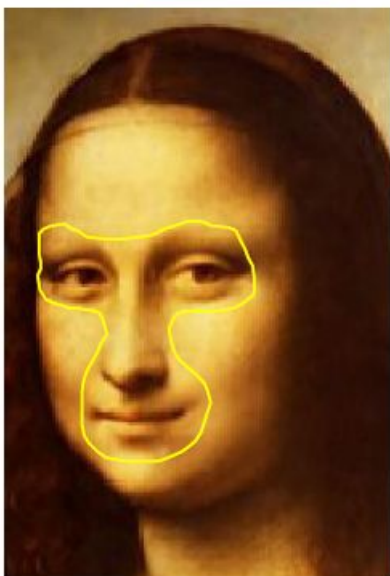
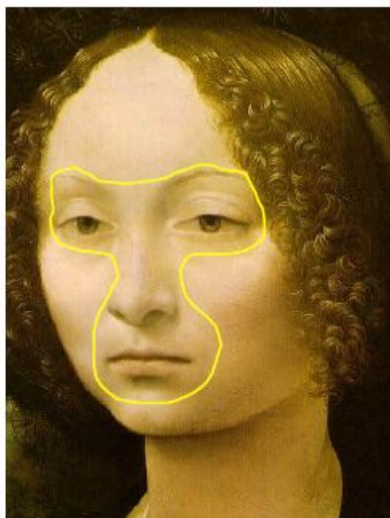
-



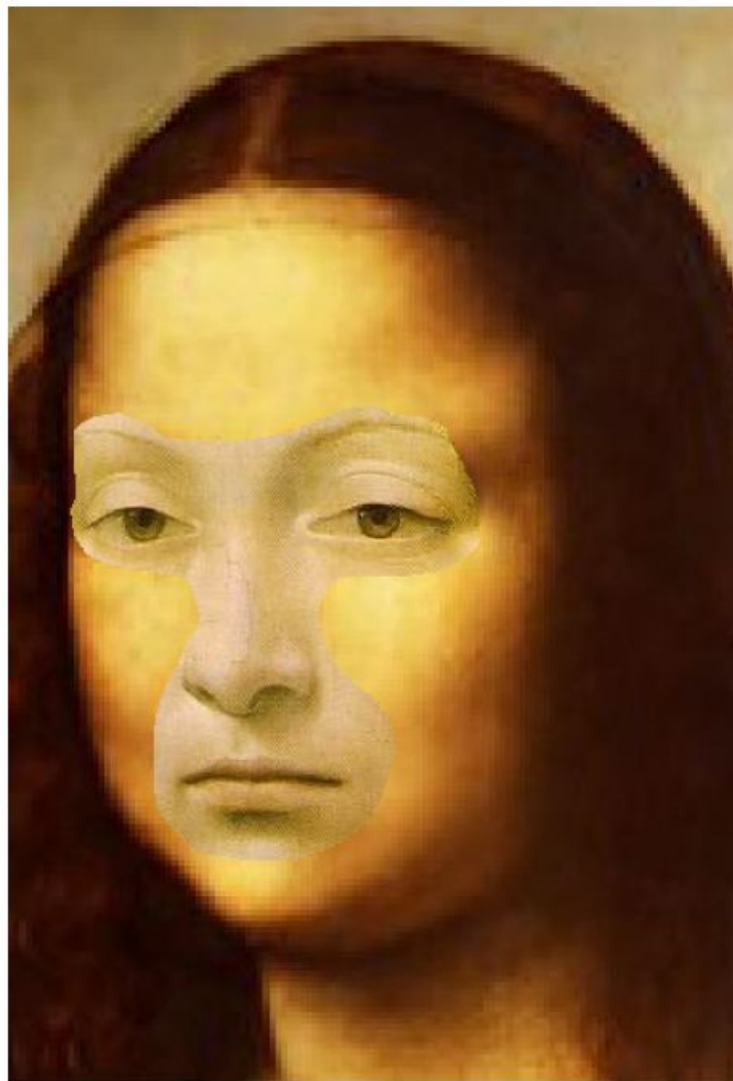
no blending

=

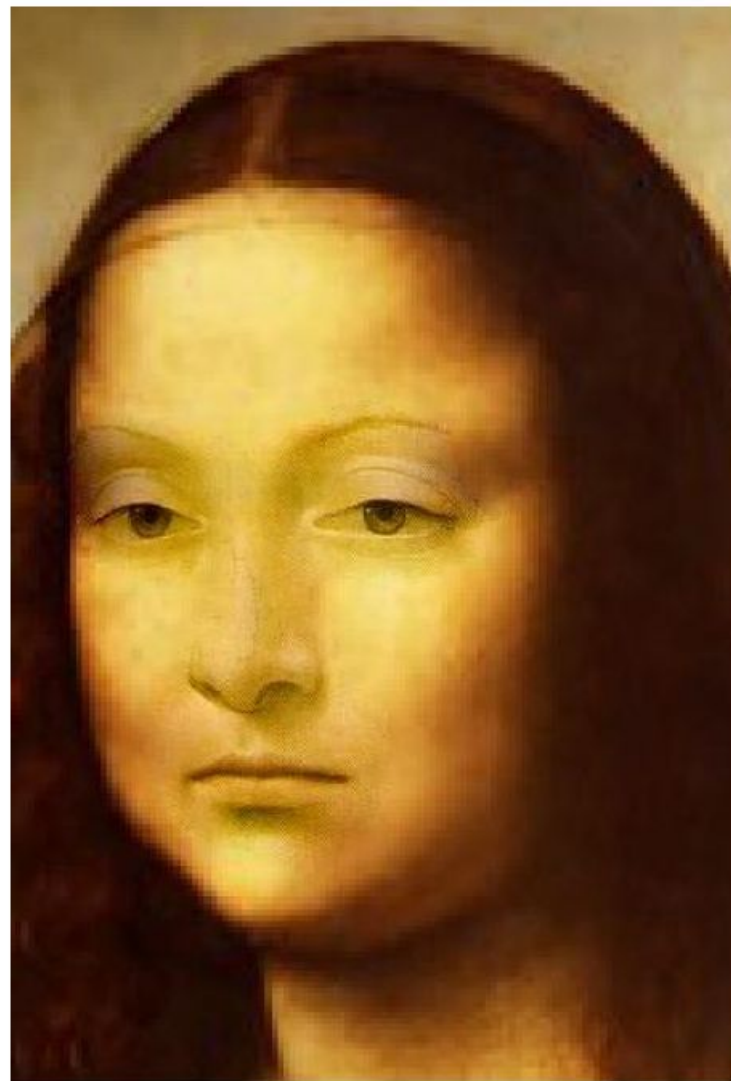




source/destination



cloning



seamless cloning

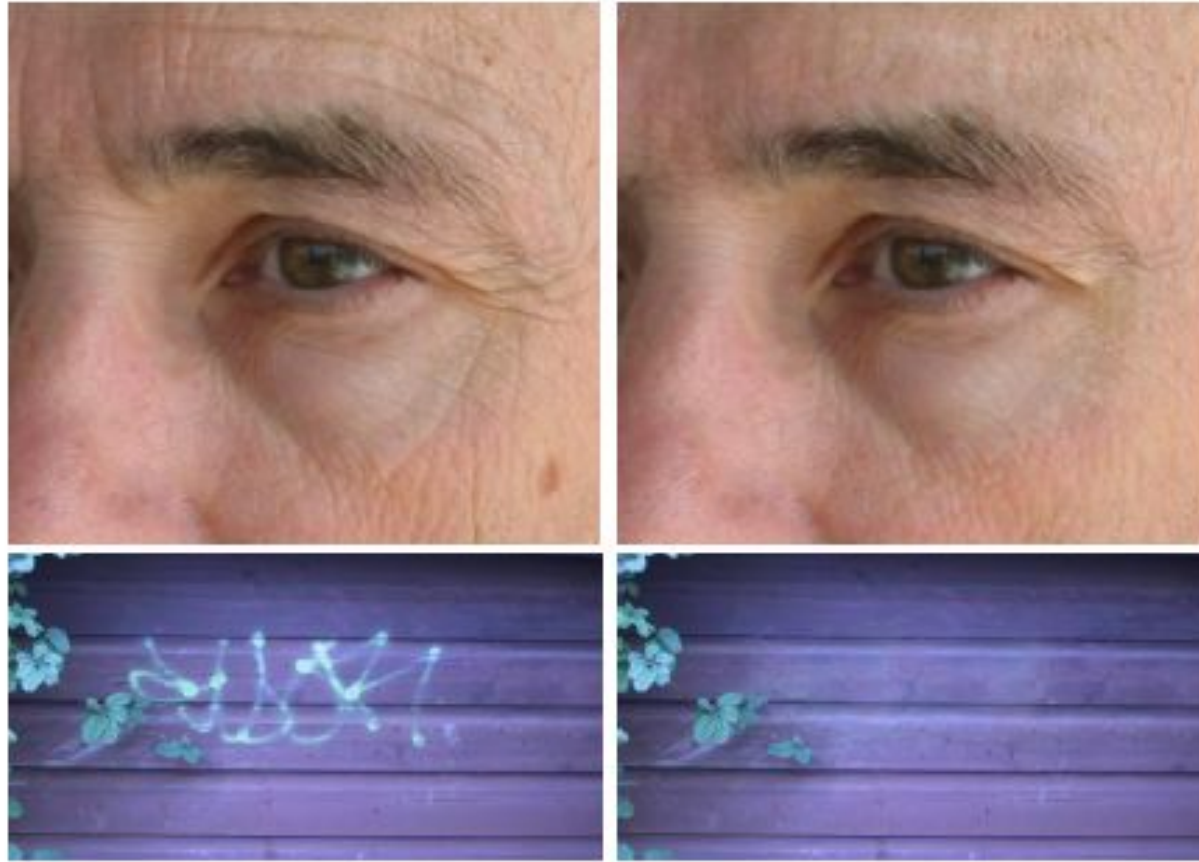


Figure 2: **Concealment.** By importing seamlessly a piece of the background, complete objects, parts of objects, and undesirable artifacts can easily be hidden. In both examples, multiple strokes (not shown) were used.

Mixing gradients



Source



Average



Mixed