Image Blending and Compositing

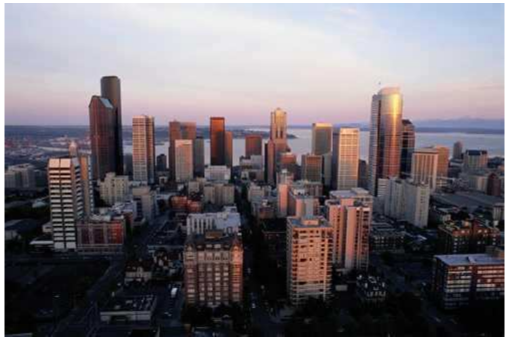
© NASA

15-463: Computational Photography
Alexei Efros, CMU, Fall 2011

Image Compositing

Compositing Procedure

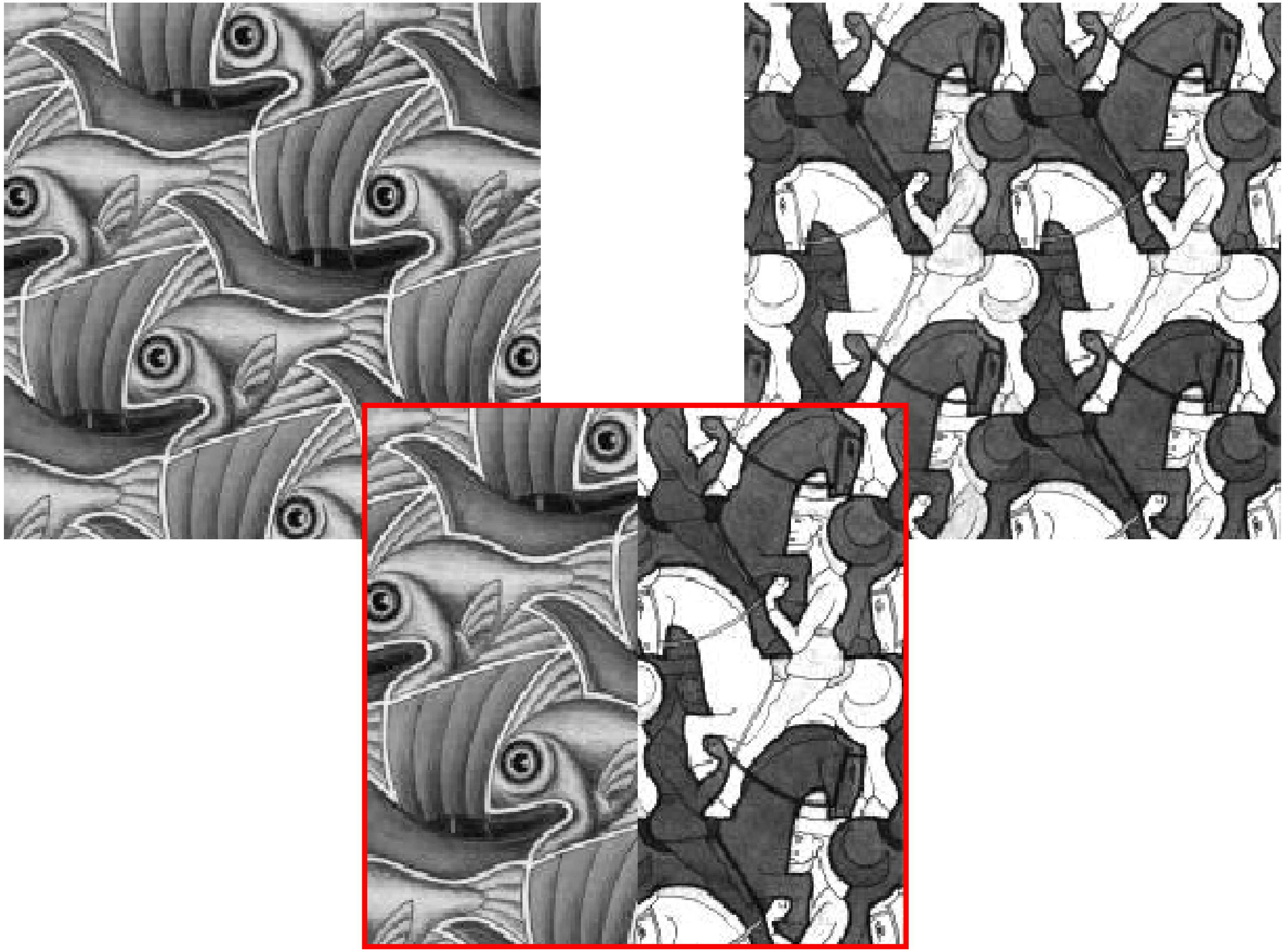
1. Extract Sprites (e.g using *Intelligent Scissors* in Photoshop)



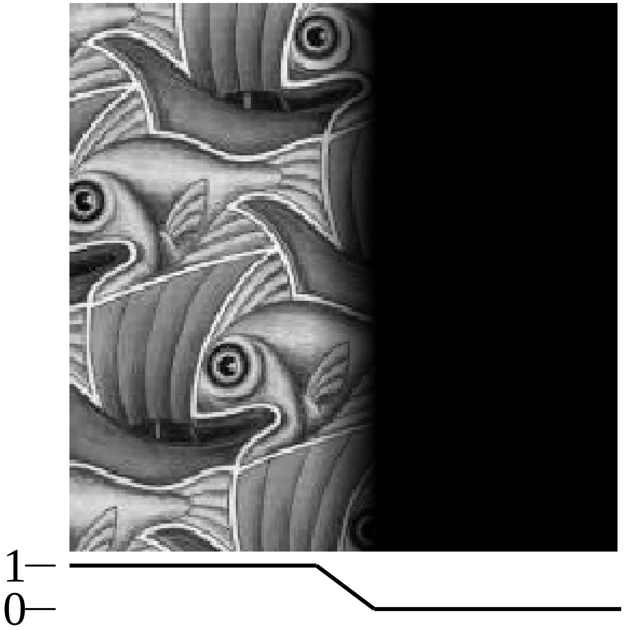
2. Blend them into the composite (in the right order)

Composite by
David Dewey

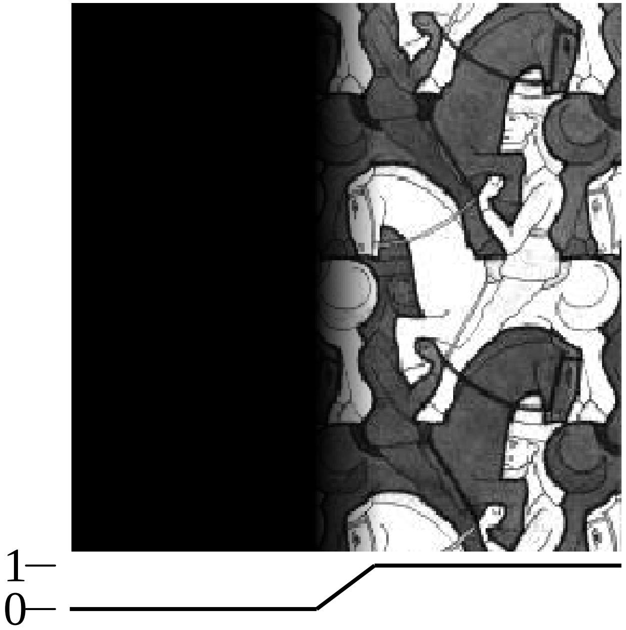
Need blending



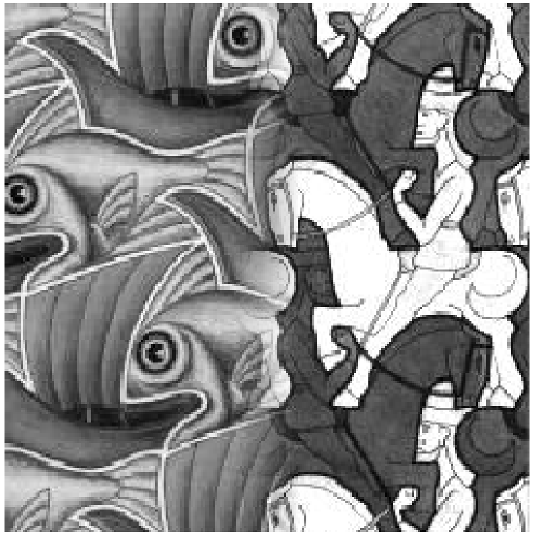
Alpha Blending / Feathering



+

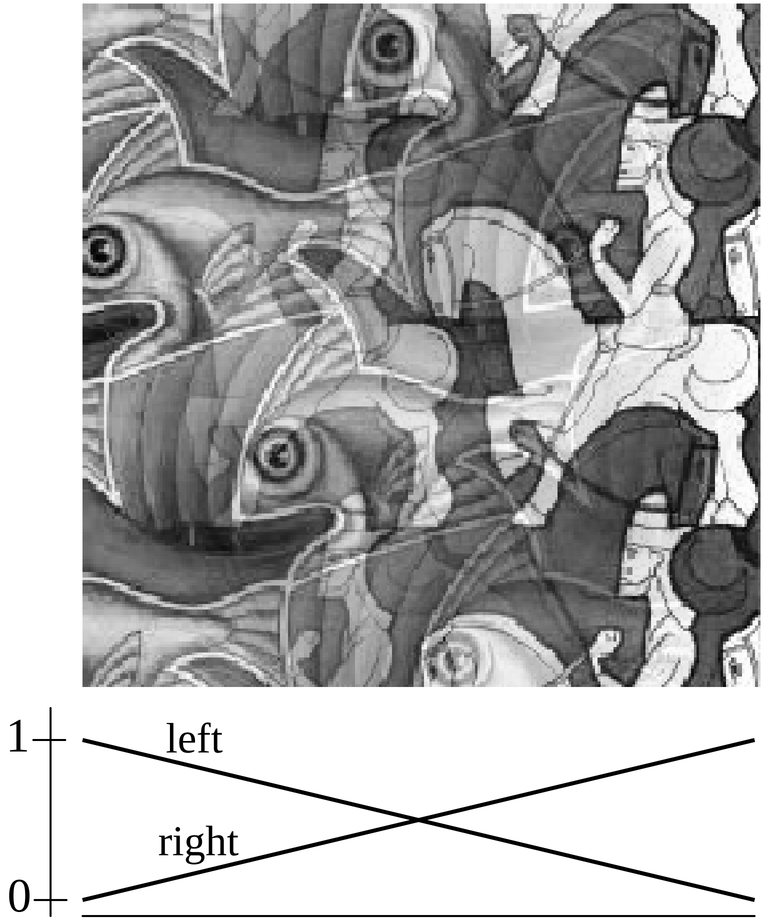


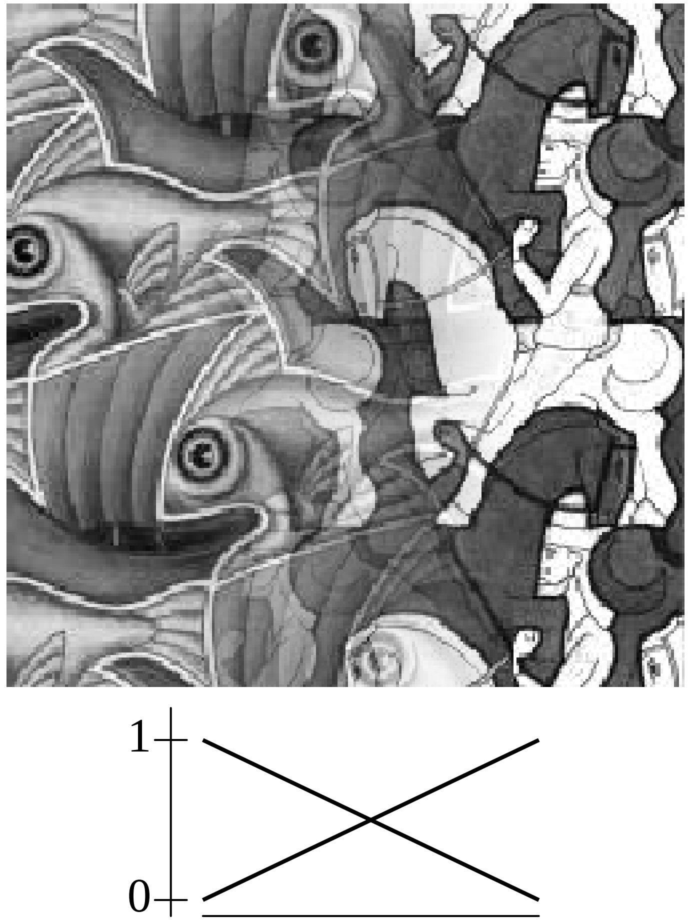
=



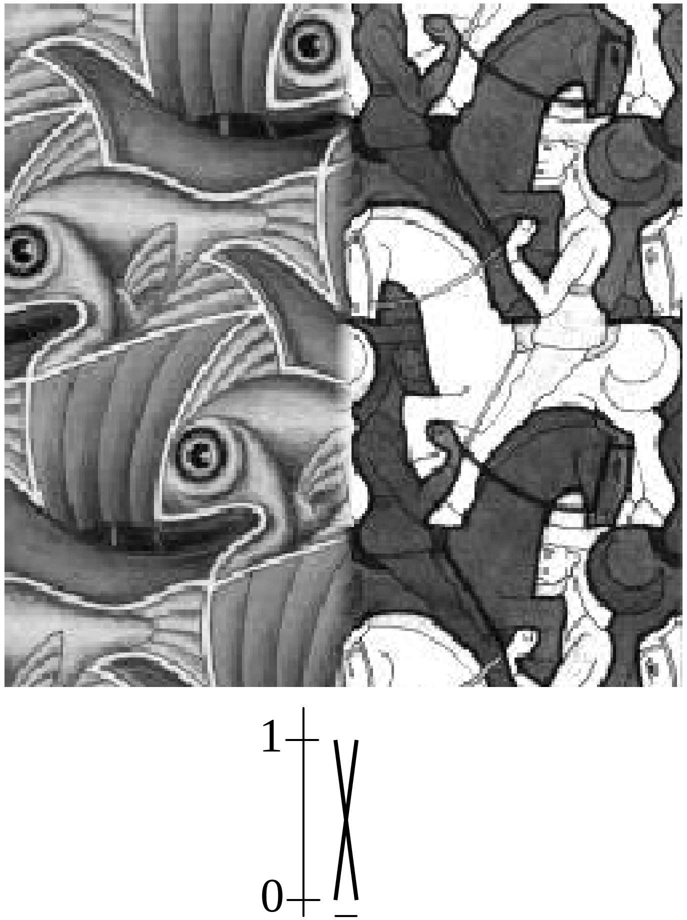
$$I_{blend} = \alpha I_{left} + (1-\alpha) I_{right}$$

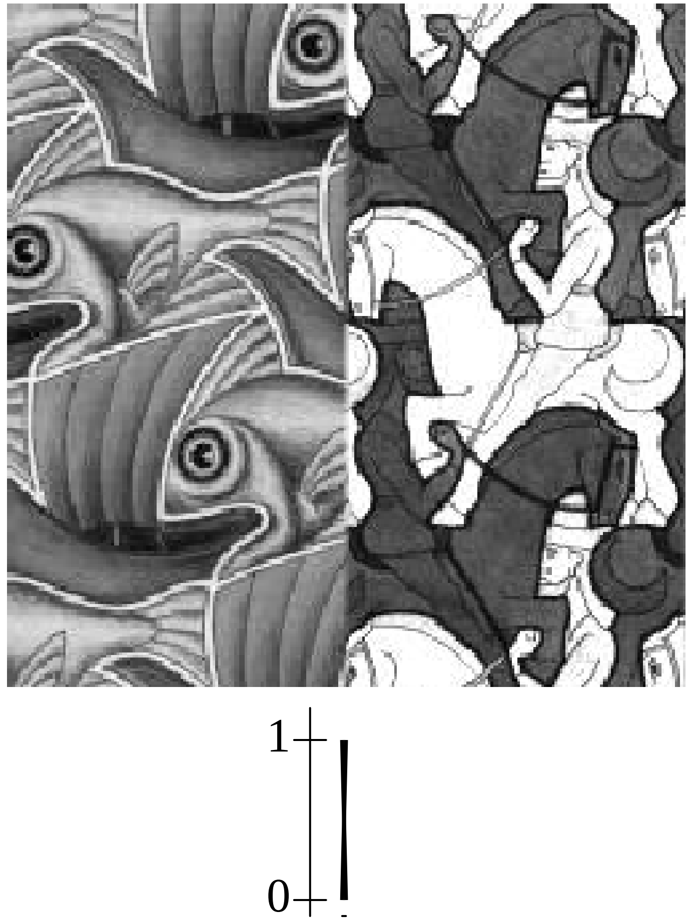
Affect of Window Size



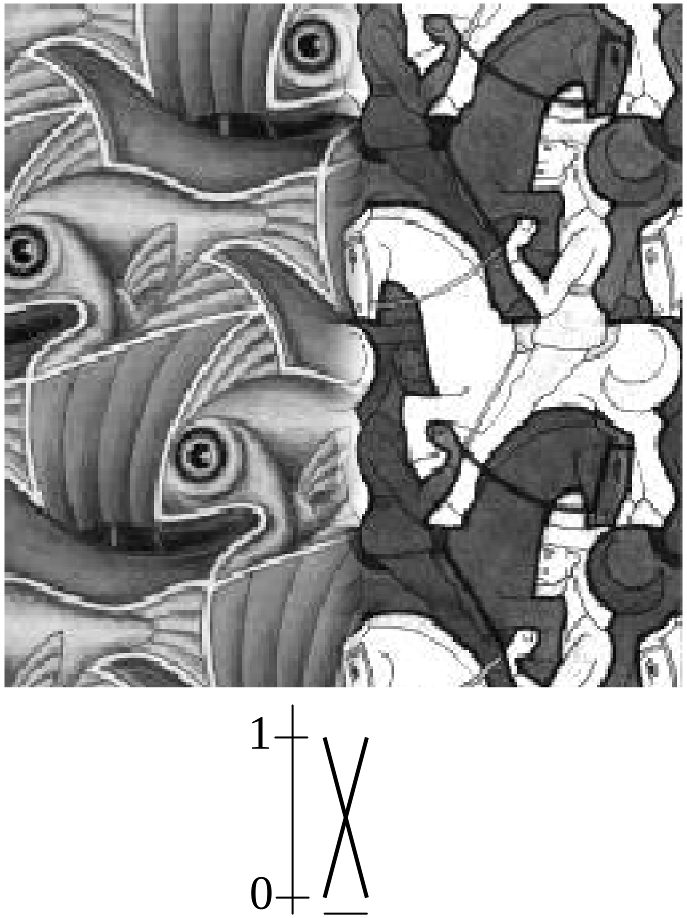


Affect of Window Size





Good Window Size



“Optimal” Window: smooth but not ghosted

What is the Optimal Window?

To avoid seams

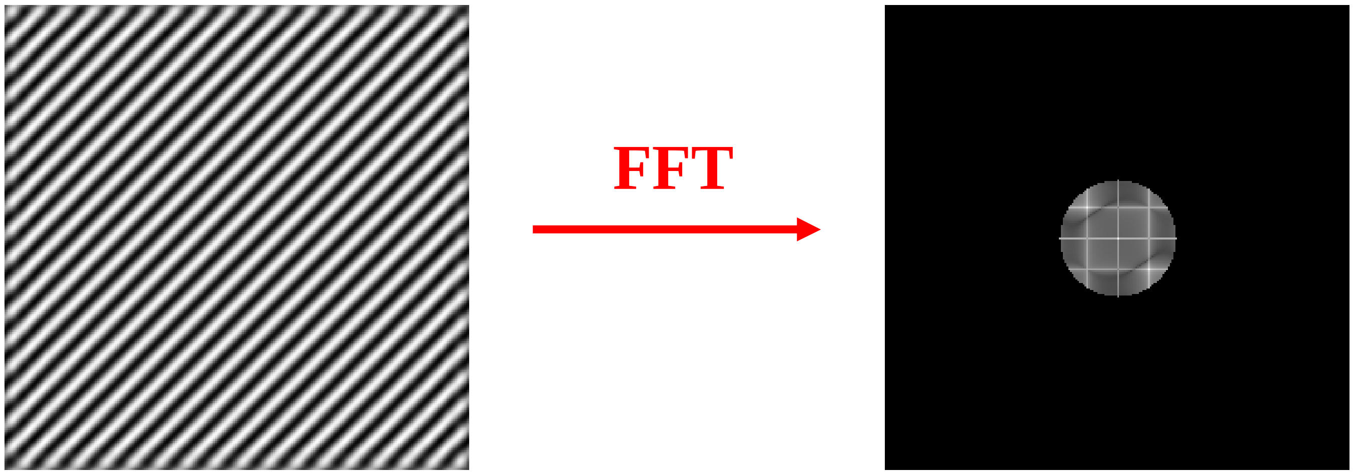
- window = size of largest prominent feature

To avoid ghosting

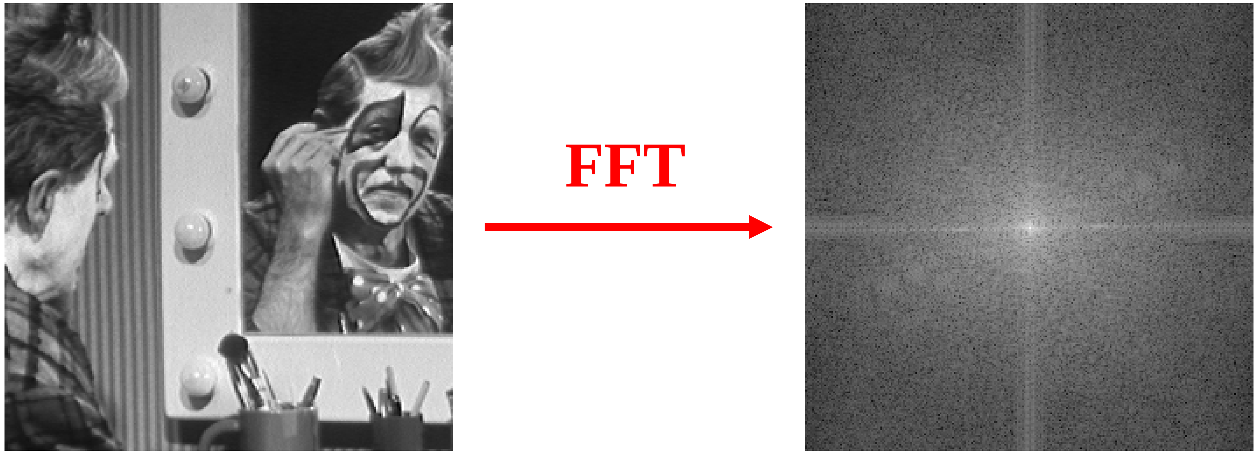
- window <= 2*size of smallest prominent feature

Natural to cast this in the *Fourier domain*

- largest frequency <= 2*size of smallest frequency
- image frequency content should occupy one “octave” (power of two)



What if the Frequency Spread is Wide



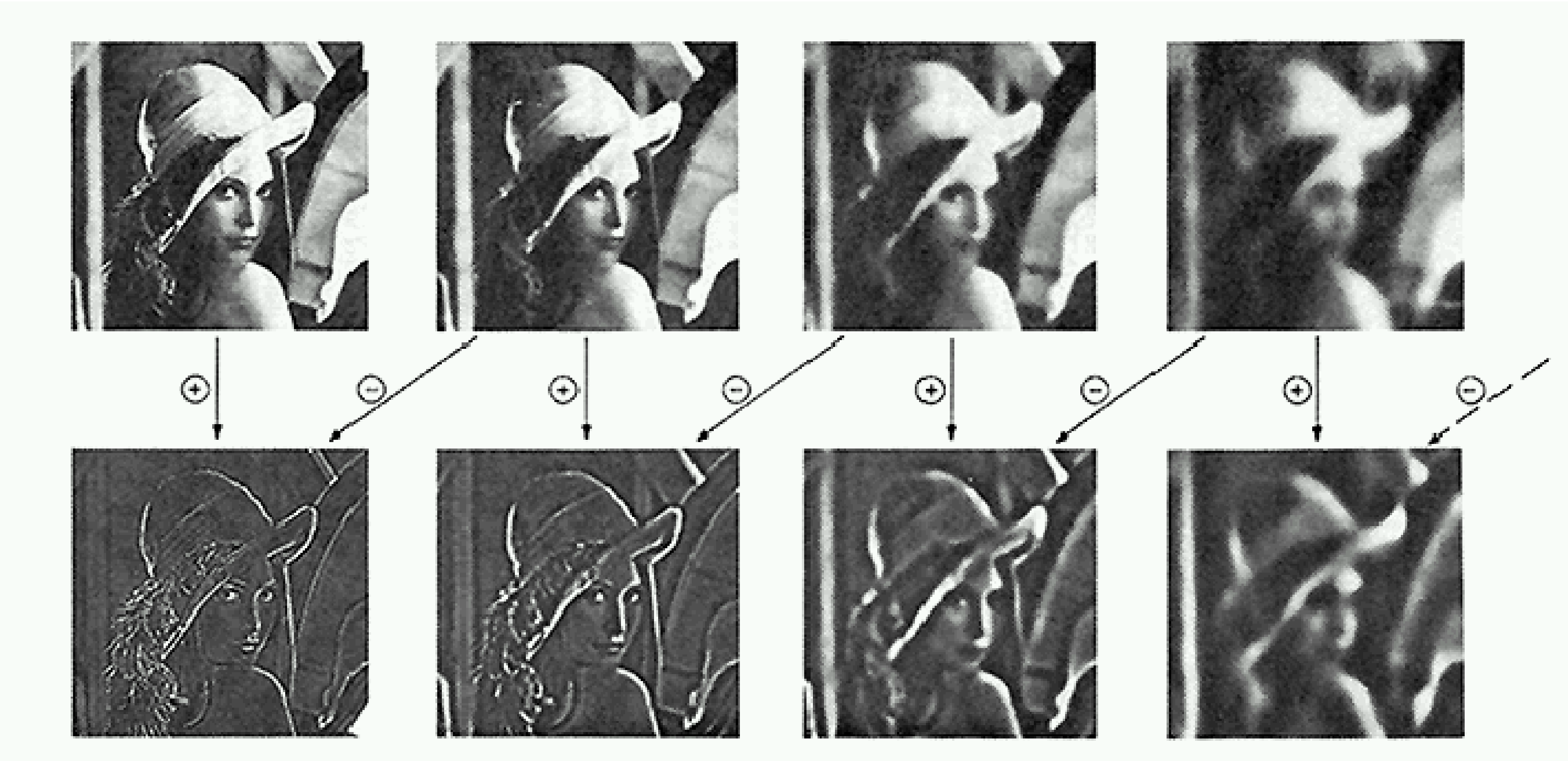
Idea (Burt and Adelson)

- Compute $F_{left} = FFT(I_{left})$, $F_{right} = FFT(I_{right})$
- Decompose Fourier image into octaves (bands)
  - $F_{left} = F_{left}^1 + F_{left}^2 + \ldots$
- Feather corresponding octaves F_{left}^i with F_{right}^i
  - Can compute inverse FFT and feather in spatial domain
- Sum feathered octave images in frequency domain

Better implemented in *spatial domain*

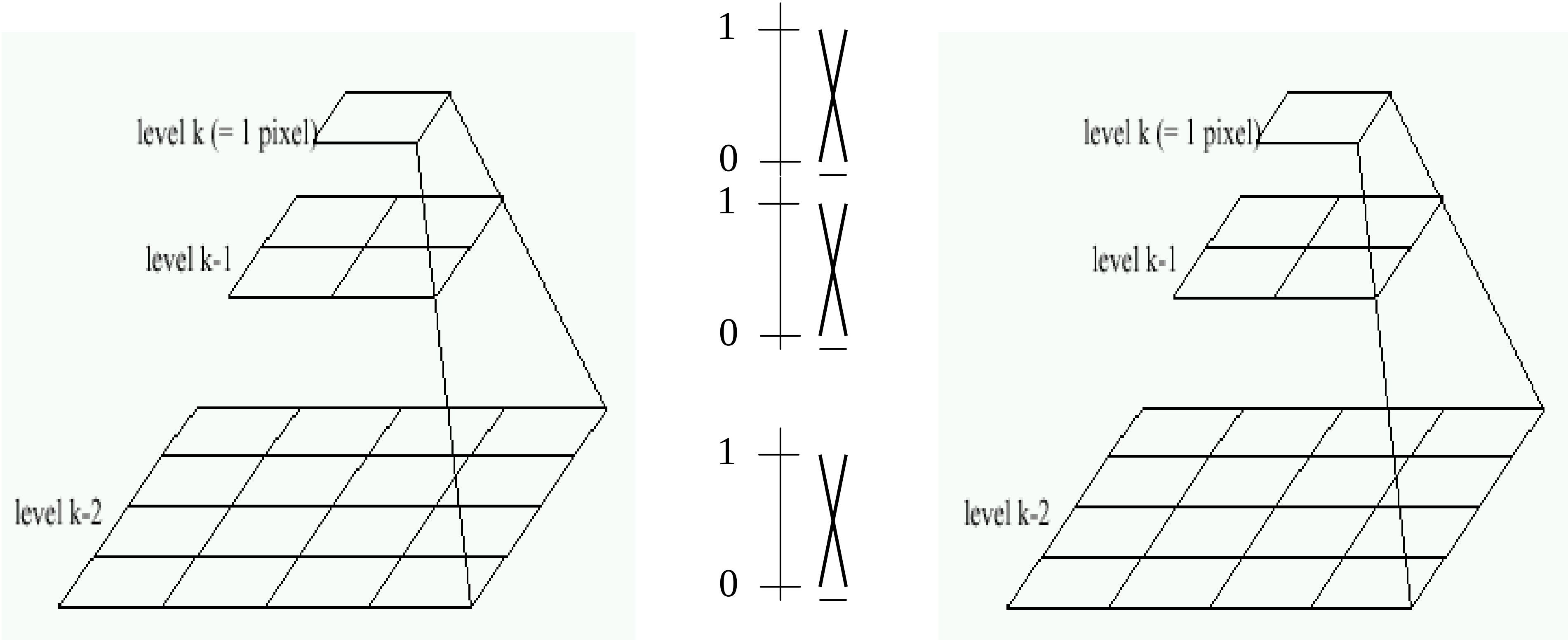
Octaves in the Spatial Domain

Lowpass Images



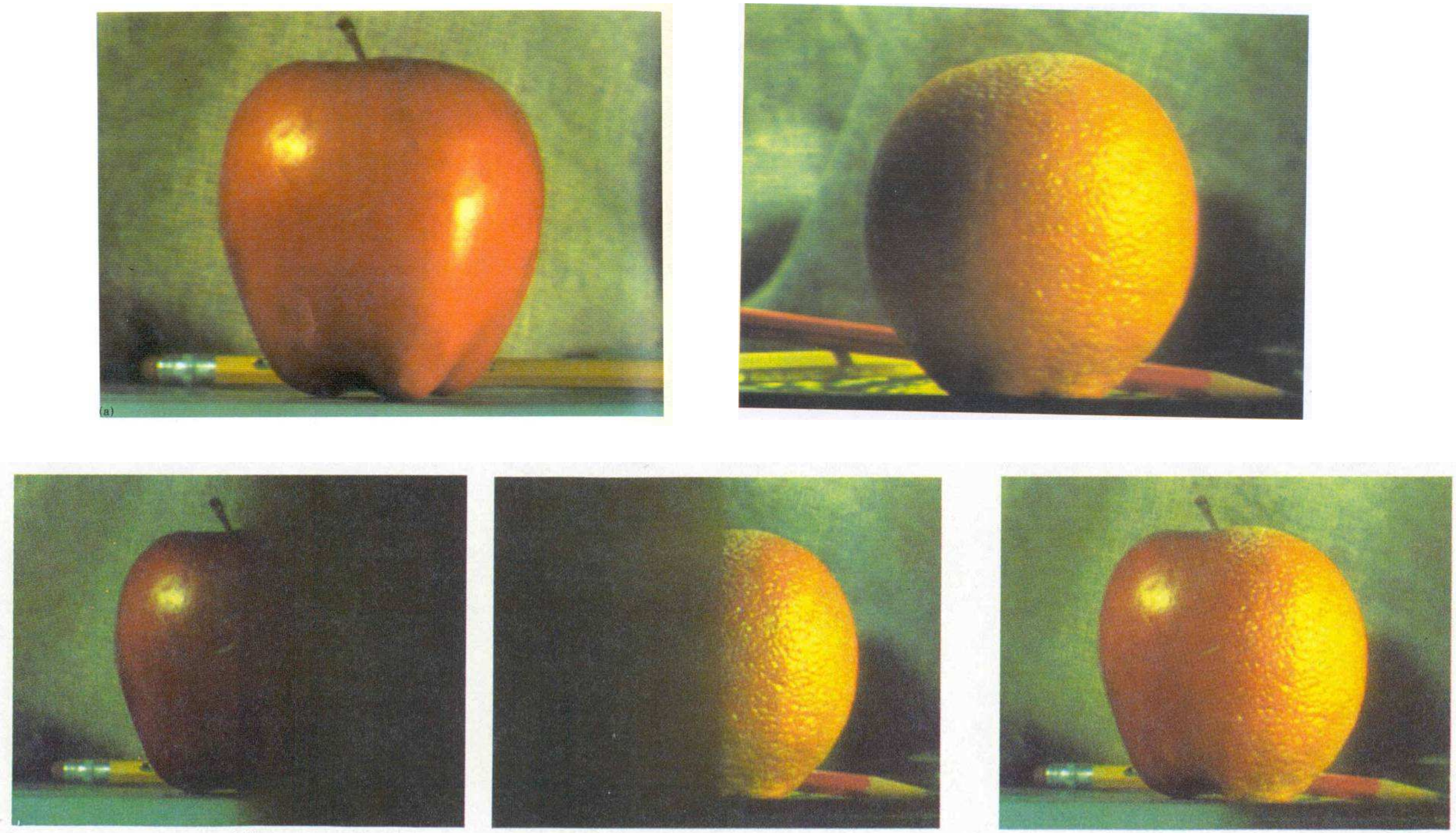
Bandpass Images

Pyramid Blending

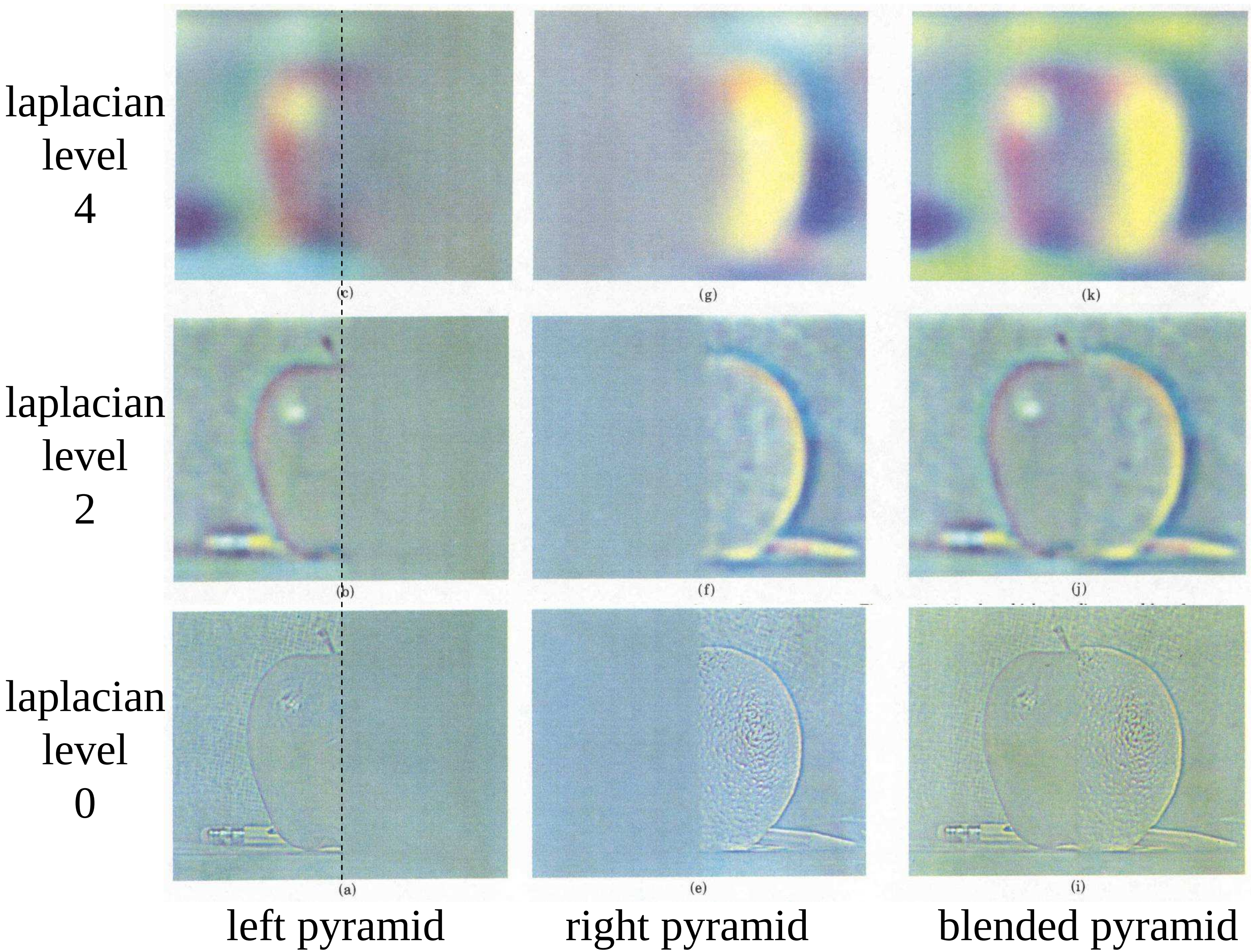


Left pyramid blend Right pyramid

Pyramid Blending



(d) (h) (l)

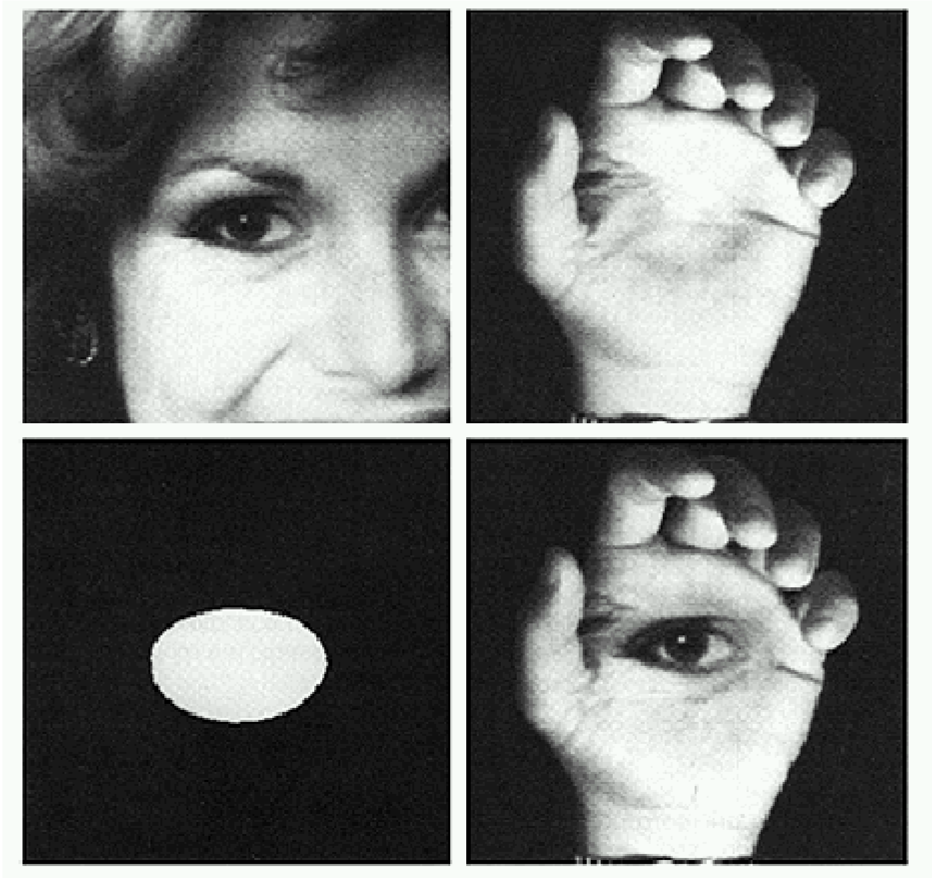

laplacian level 4
laplacian level 2
laplacian level 0
(c)
(g)
(k)
(b)
(f)
(j)
(a)
(e)
(i)
left pyramid
right pyramid
blended pyramid

Laplacian Pyramid: Blending

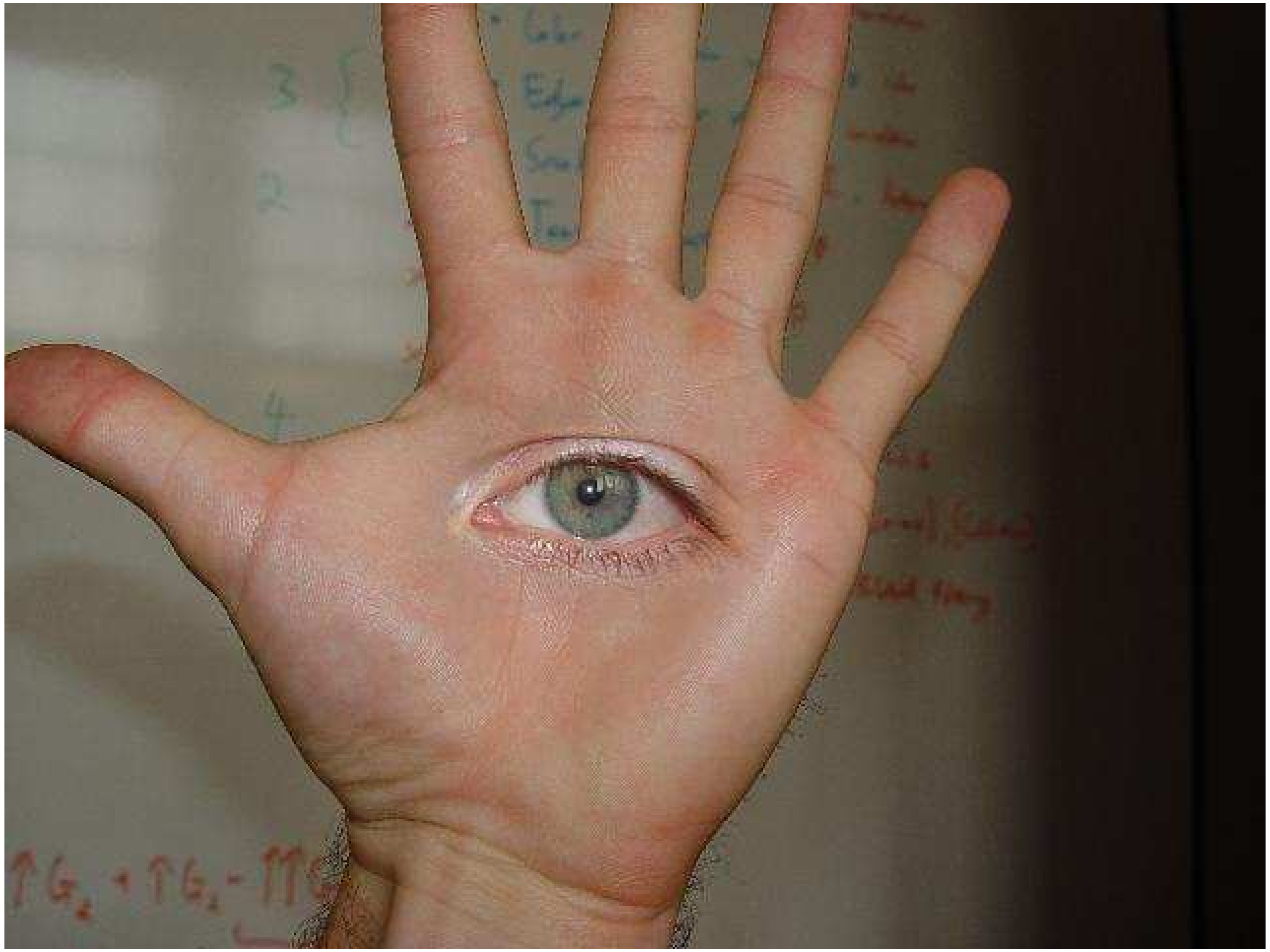
General Approach:

1. Build Laplacian pyramids *LA* and *LB* from images *A* and *B*
2. Build a Gaussian pyramid *GR* from selected region *R*
3. Form a combined pyramid *LS* from *LA* and *LB* using nodes of *GR* as weights:
   - *LS(i,j) = GR(I,j,)*LA(I,j) + (1-GR(I,j))*LB(I,j)*
4. Collapse the *LS* pyramid to get the final blended image

Blending Regions



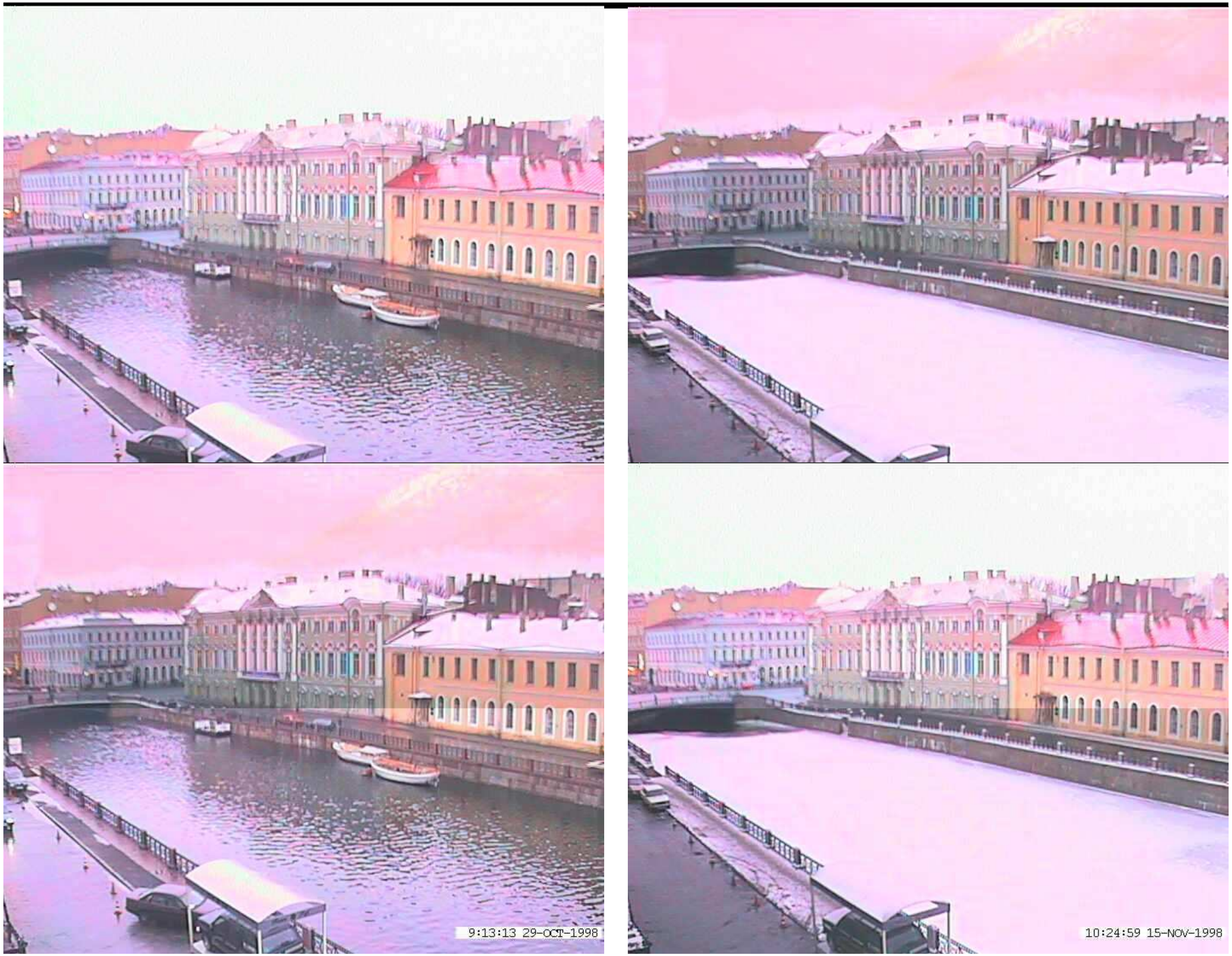
Horror Photo



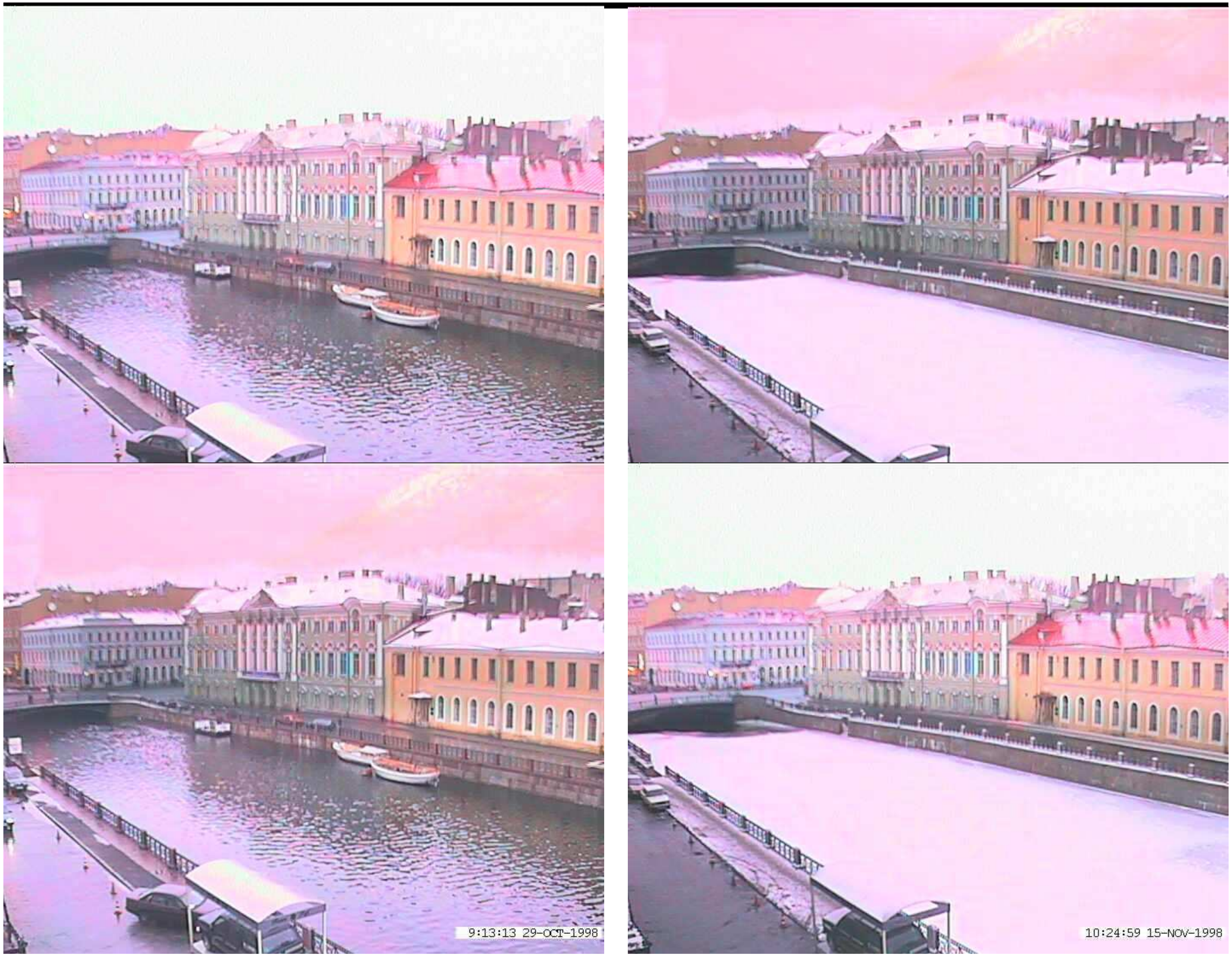
© david dmartin (Boston College)

Results from this class (fall 2005)

Season Blending (St. Petersburg)



Season Blending (St. Petersburg)



Simplification: Two-band Blending

Brown & Lowe, 2003

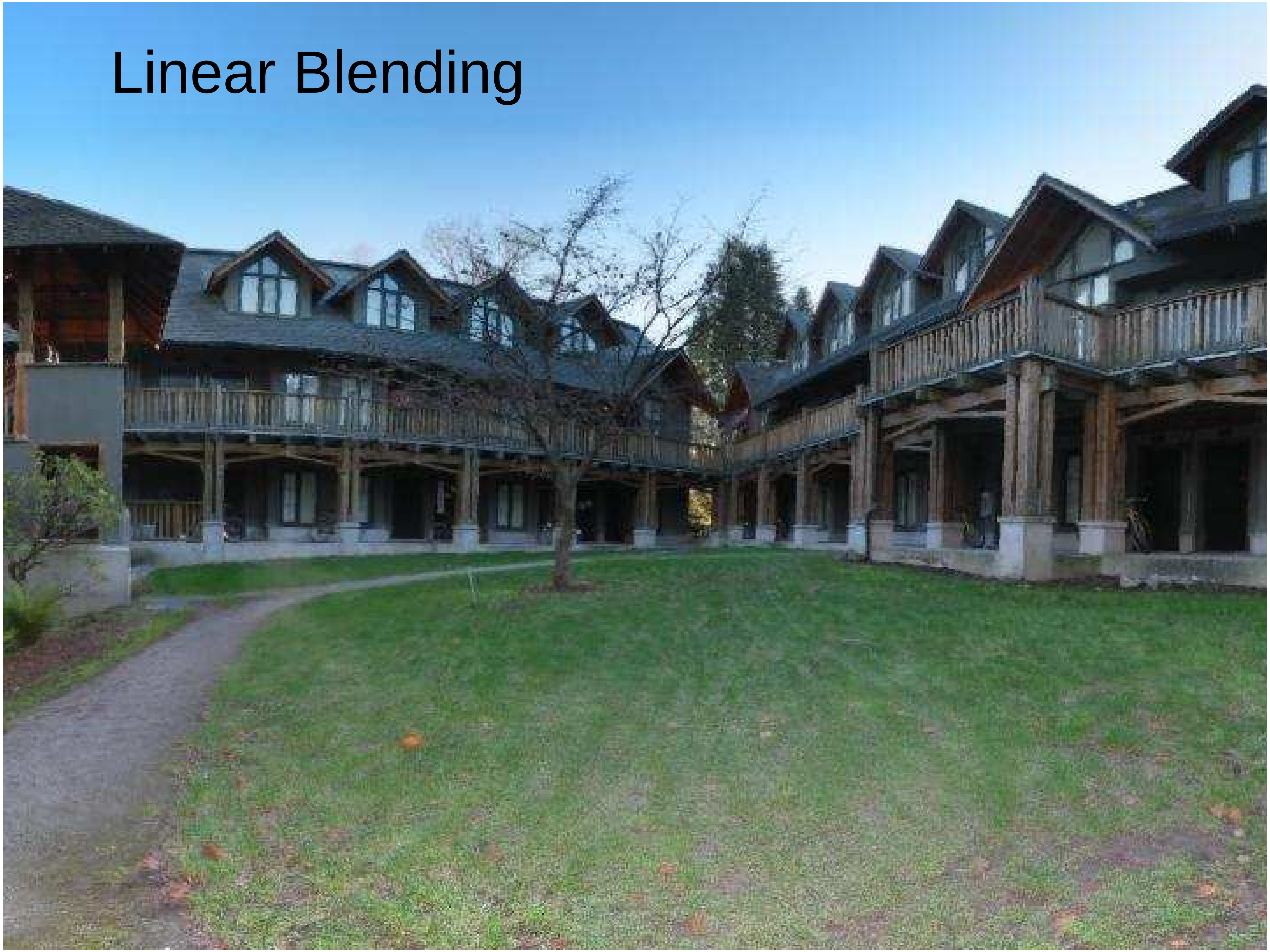
- Only use two bands: high freq. and low freq.
- Blends low freq. smoothly
- Blend high freq. with no smoothing: use binary alpha

2-band Blending

Low frequency ($\lambda > 2$ pixels)

High frequency ($\lambda < 2$ pixels)

Linear Blending



2-band Blending

Don't blend, CUT!

Moving objects become ghosts

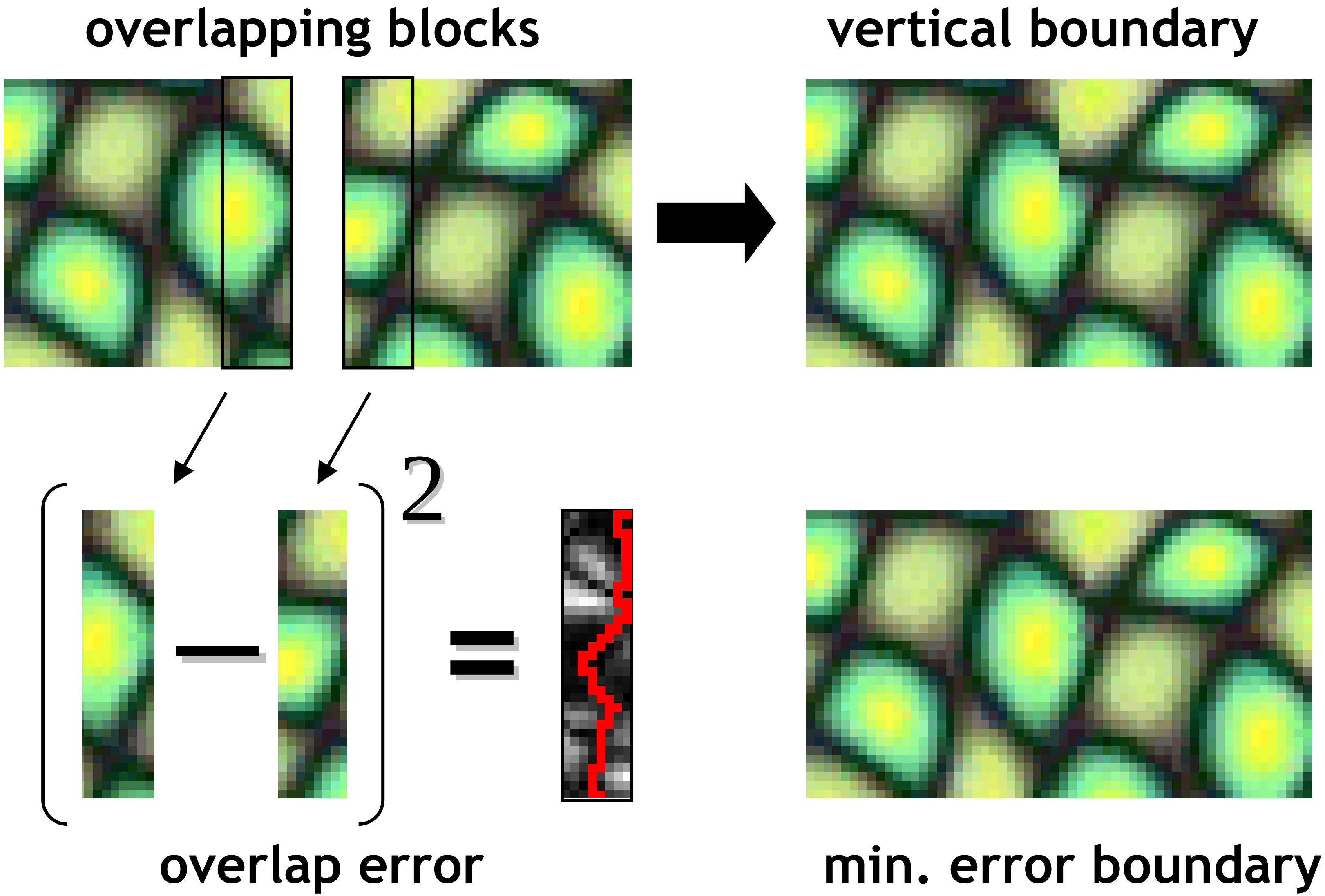
So far we only tried to blend between two images.
What about finding an optimal seam?

Davis, 1998

Segment the mosaic

- Single source image per segment
- Avoid artifacts along boundries
  - Dijkstra's algorithm

Minimal error boundary



Seam Carving

Seam Carving for Content-Aware Image Resizing

Shai Avidan
Mitsubishi Electric Research Labs

Ariel Shamir
The Interdisciplinary Center & MERL

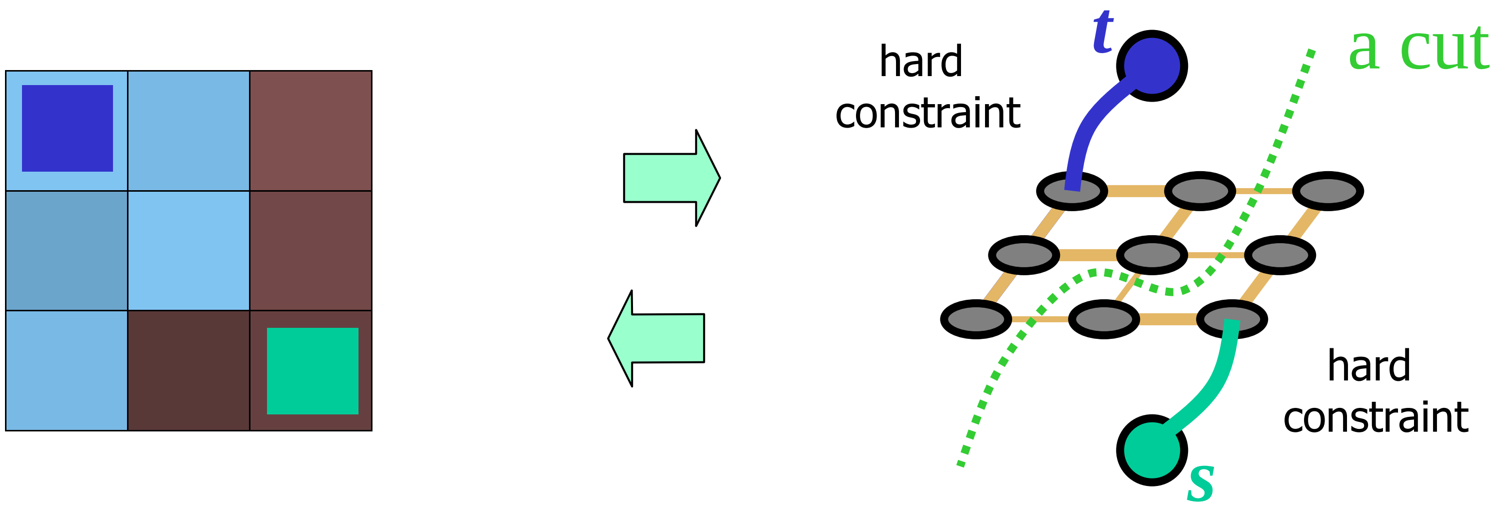
http://www.youtube.com/watch?v=6NcIJXTlugc

Graphcuts

What if we want similar “cut-where-things-agree” idea, but for closed regions?

- Dynamic programming can’t handle loops

Graph cuts – a more general solution



Minimum cost cut can be computed in polynomial time

(max-flow/min-cut algorithms)

Kwatra et al, 2003

Actually, for this example, DP will work just as well…

Lazy Snapping

(a) Girl (4/2/12) (b) Ballet (4/7/14) (c) Boy (6/2/13)

(c) Grandpa (4/2/11) (d) Twins (4/4/12)

Interactive segmentation using graphcuts

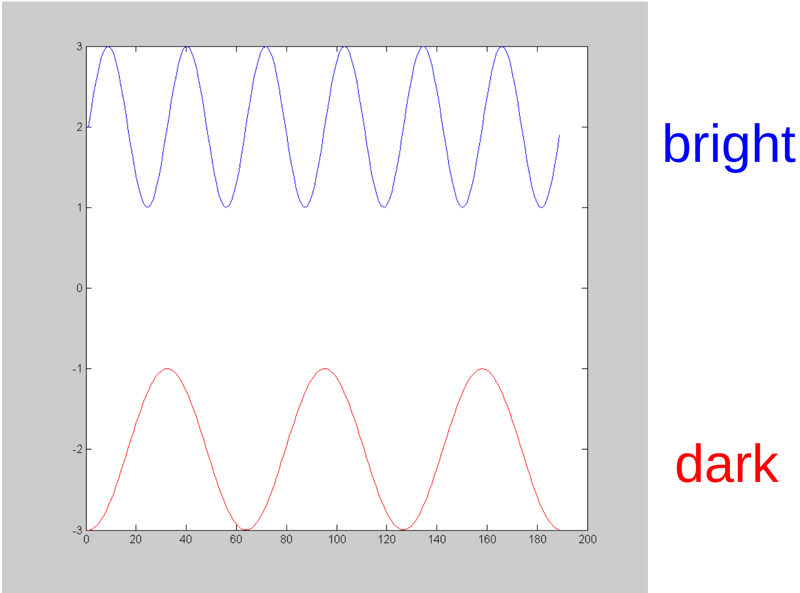
Gradient Domain

In Pyramid Blending, we decomposed our image into 2^{nd} derivatives (Laplacian) and a low-res image

Let us now look at 1^{st} derivatives (gradients):

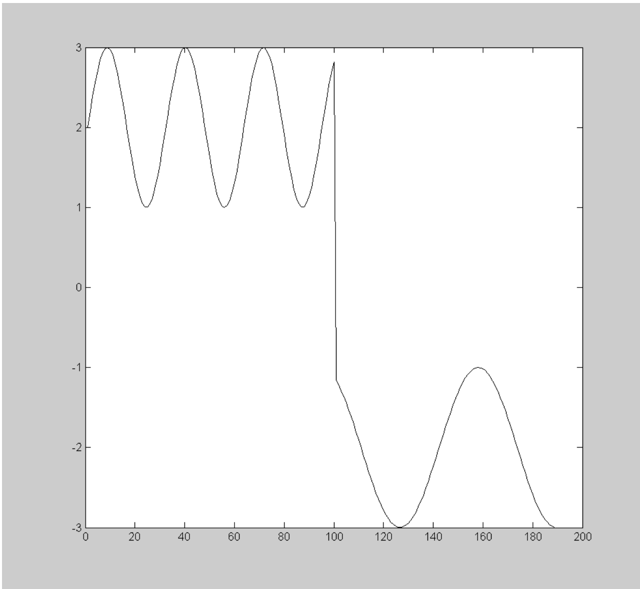
- No need for low-res image
  - captures everything (up to a constant)
- Idea:
  - Differentiate
  - Blend / edit / whatever
  - Reintegrate

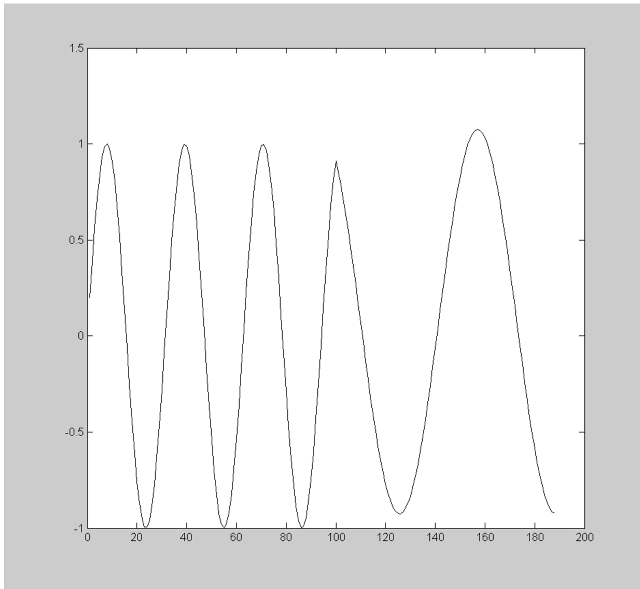
Gradient Domain blending (1D)



Two signals

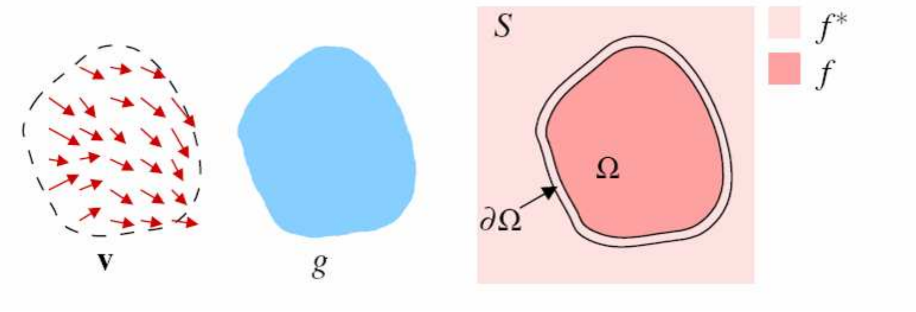
Regular blending





Blending derivatives

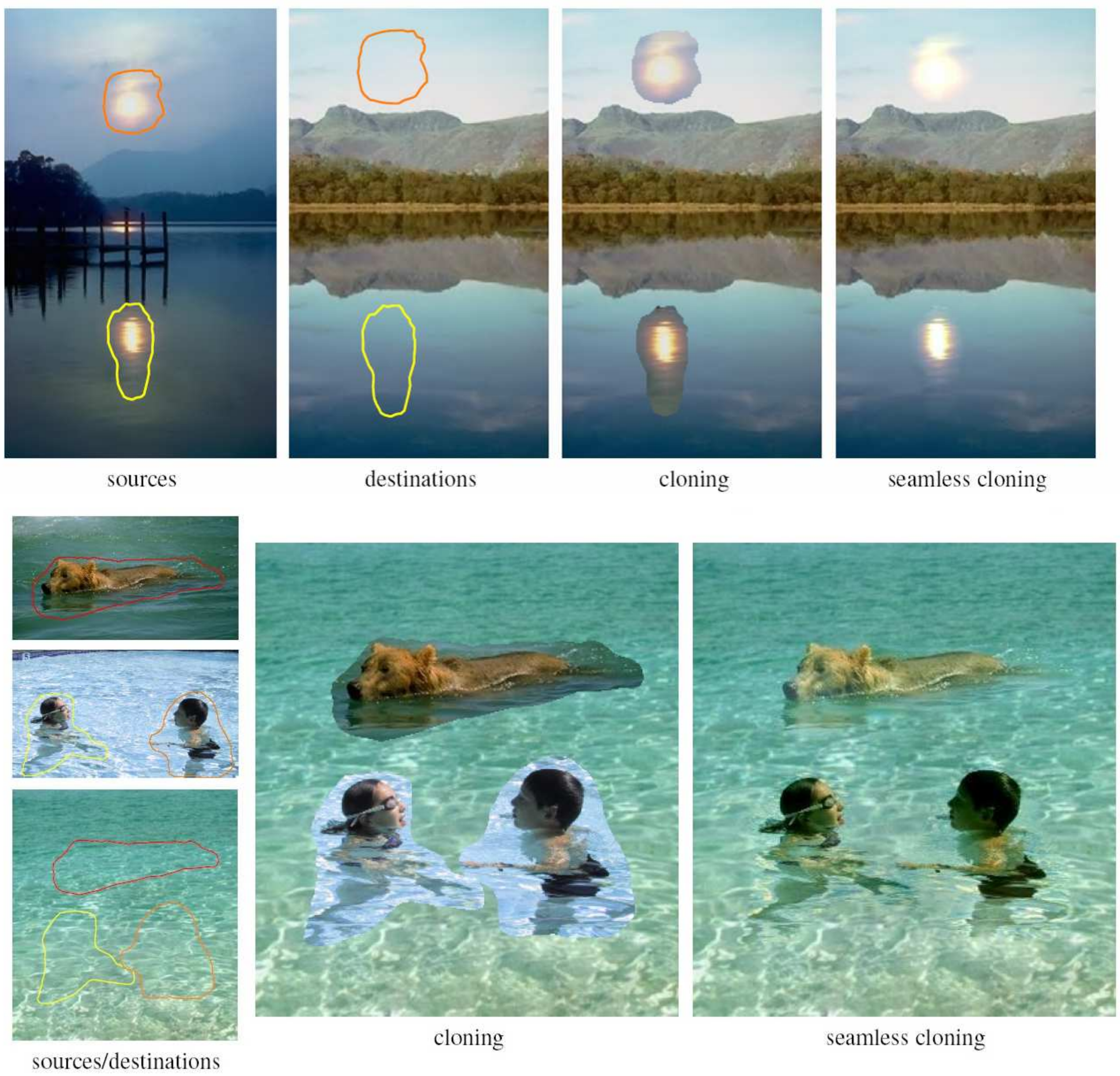
Gradient Domain Blending (2D)



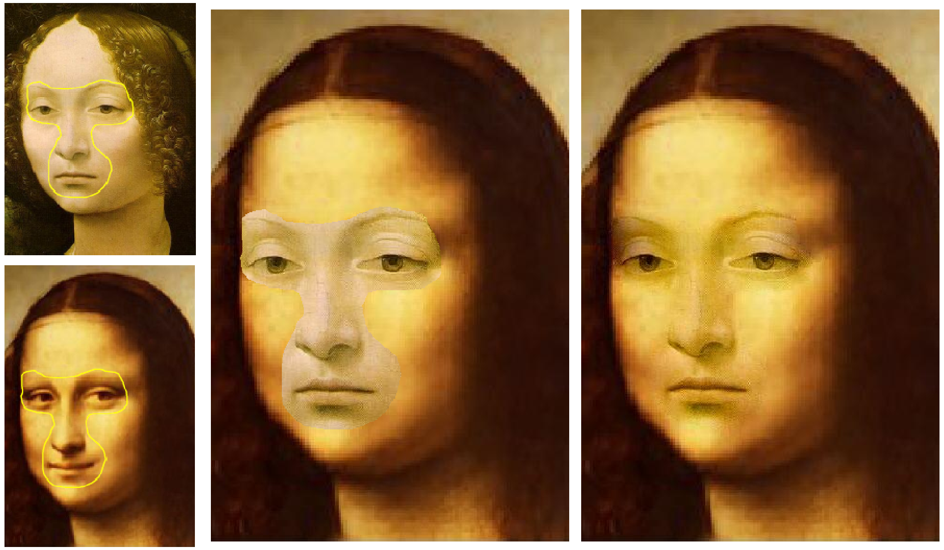
Trickier in 2D:

- Take partial derivatives dx and dy (the gradient field)
- Fidle around with them (smooth, blend, feather, etc)
- Reintegrate
  - But now integral(dx) might not equal integral(dy)
- Find the most agreeable solution
  - Equivalent to solving Poisson equation
  - Can be done using least-squares

Perez et al., 2003



Perez et al, 2003



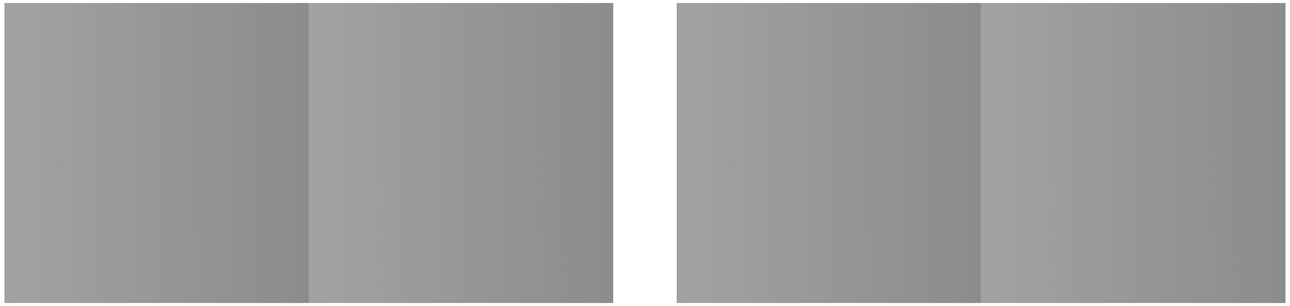
source/destination cloning seamless cloning

editing

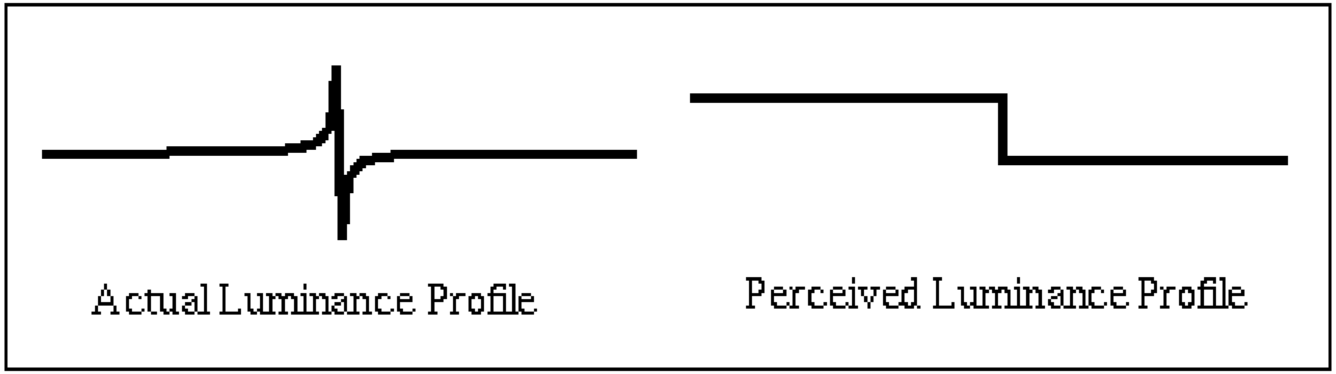
Limitations:

- Can’t do contrast reversal (gray on black -> gray on white)
- Colored backgrounds “bleed through”
- Images need to be very well aligned

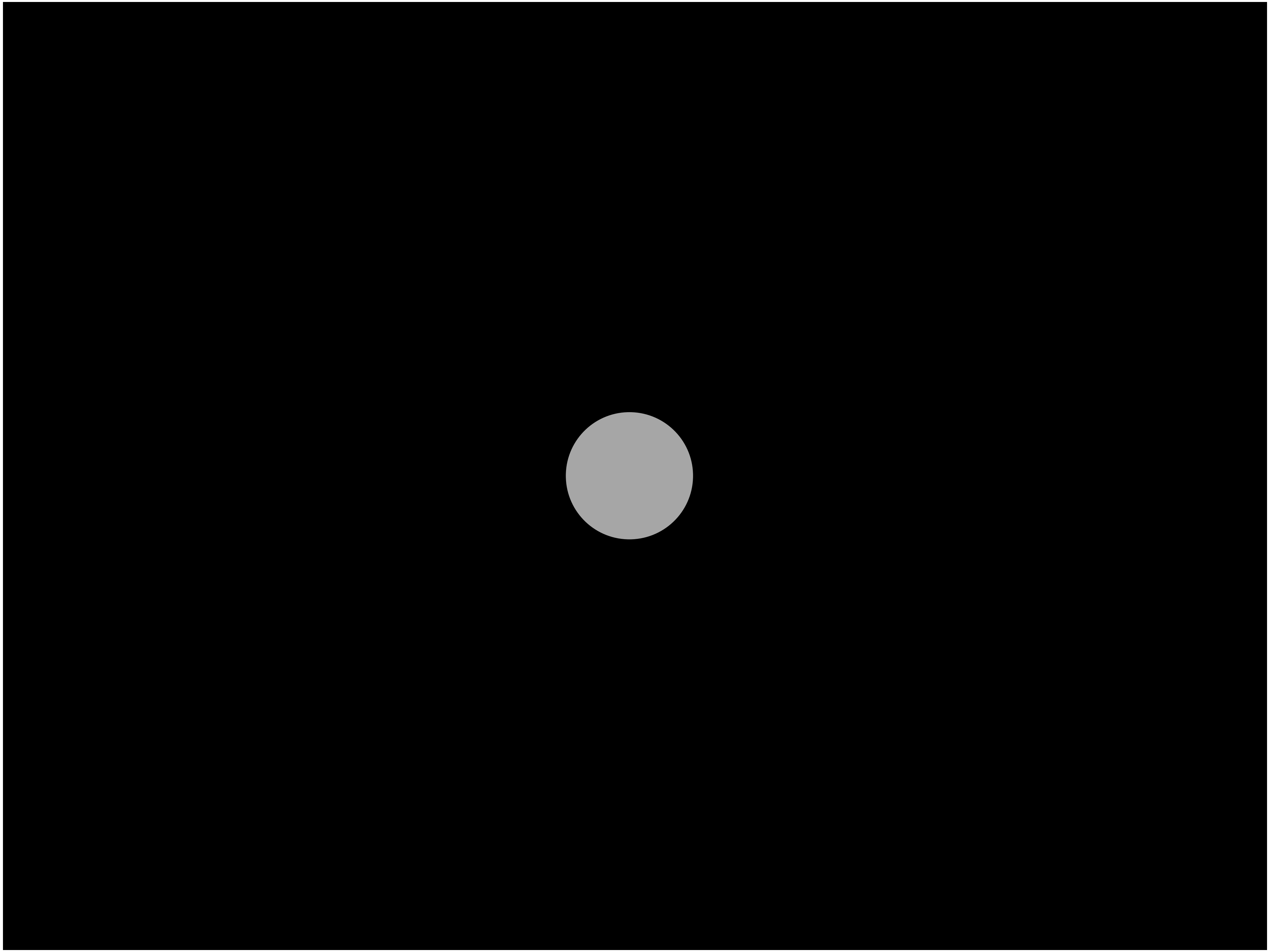
Gradients vs. Pixels

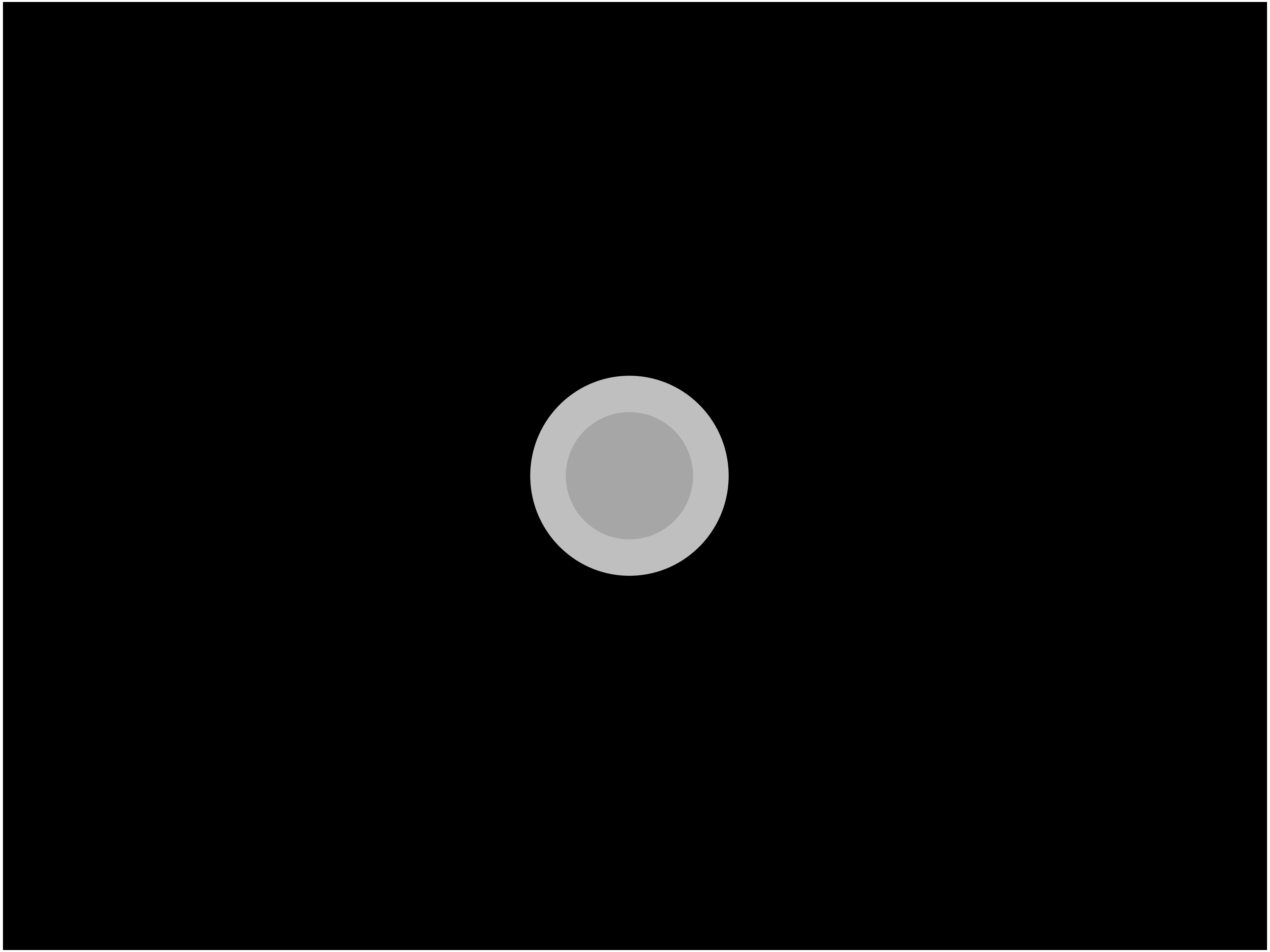


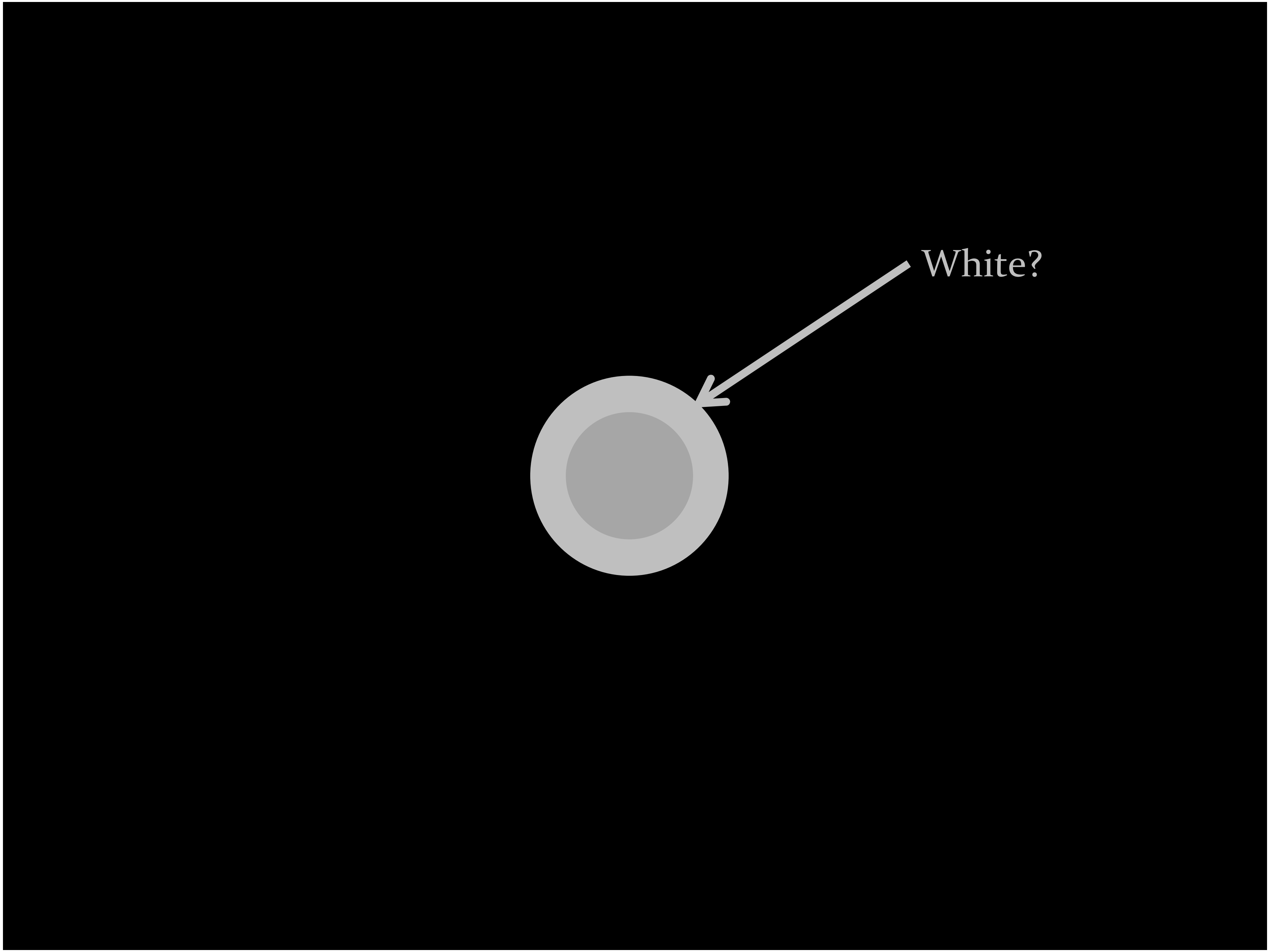
Craik-O'Brien Cornsweet Effect

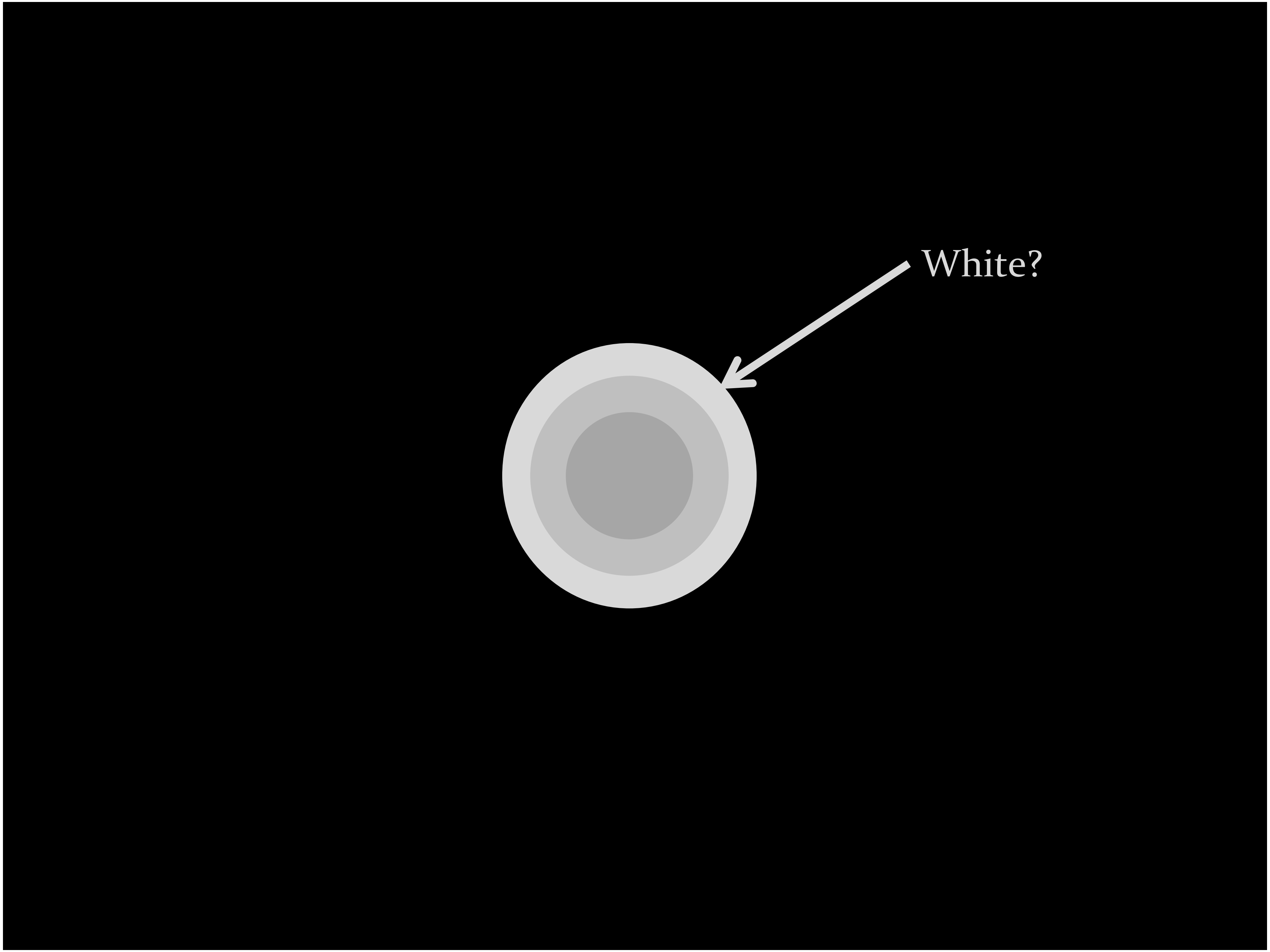


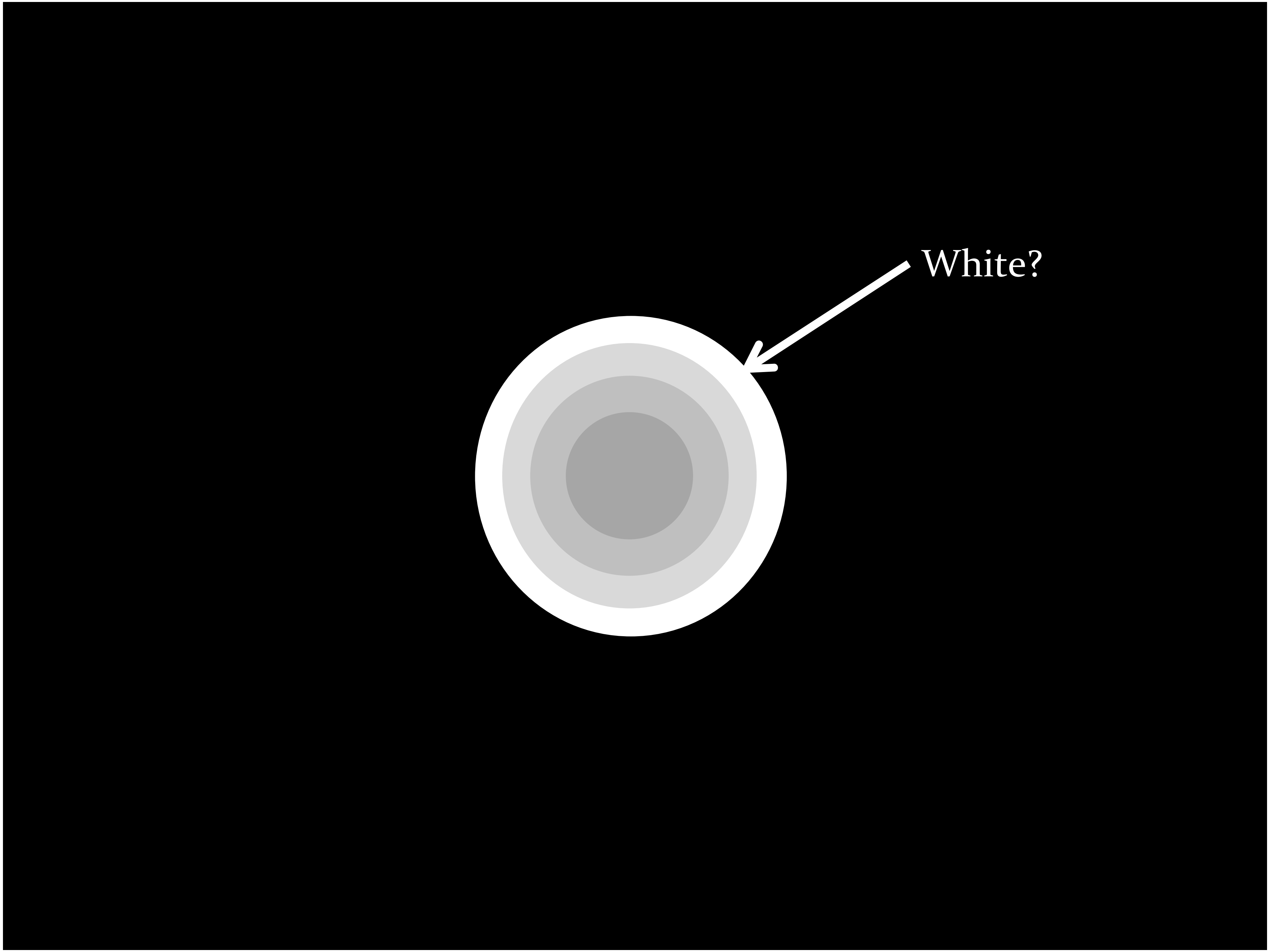
Can we use this for range compression?

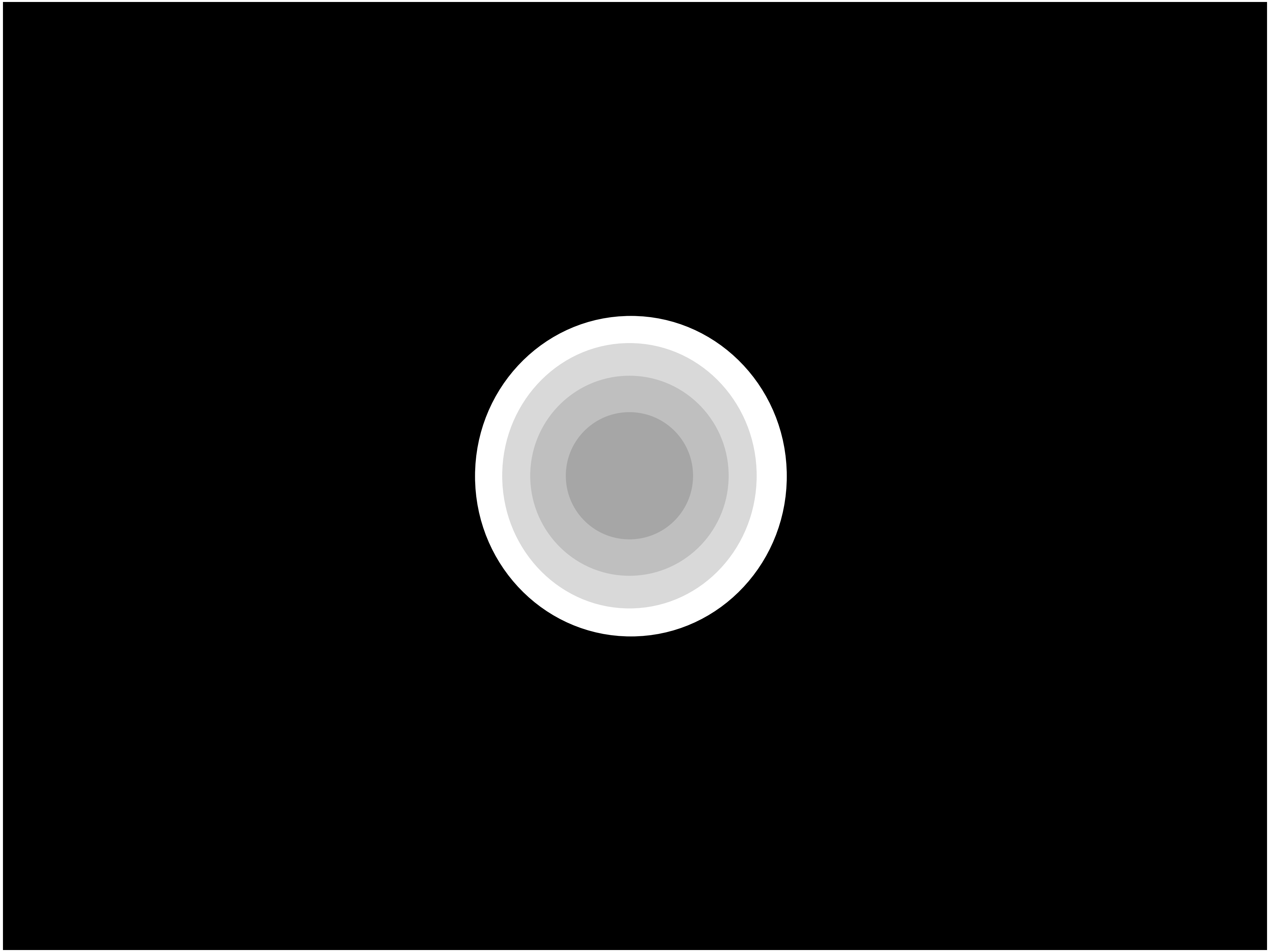




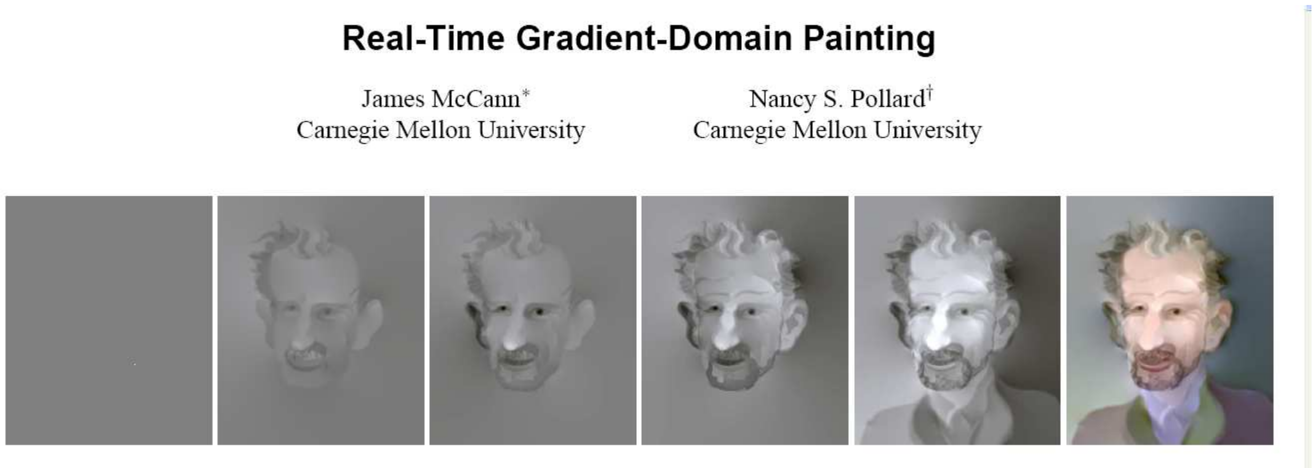

White?


White?


White?



Thinking in Gradient Domain


Real-Time Gradient-Domain Painting

James McCann*
Carnegie Mellon University

Nancy S. Pollard†
Carnegie Mellon University

Our very own Jim McCann::

James McCann

Real-Time Gradient-Domain Painting,

SIGGRAPH 2009

Gradient Domain as Image Representation

See GradientShop paper as good example:

GradientShop: A Gradient-Domain Optimization Framework for Image and Video Filtering

Pravin Bhat[1] C. Lawrence Zitnick[2] Michael Cohen[1,2] Brian Curless[1]
[1]University of Washington [2]Microsoft Research

http://www.gradientshop.com/

Motivation for gradient-domain filtering?

- Can be used to exert high-level control over images

Motivation for gradient-domain filtering?

- Can be used to exert high-level control over images
  - gradients – low level image-features

Motivation for gradient-domain filtering?

- Can be used to exert high-level control over images
  - gradients – low level image-features

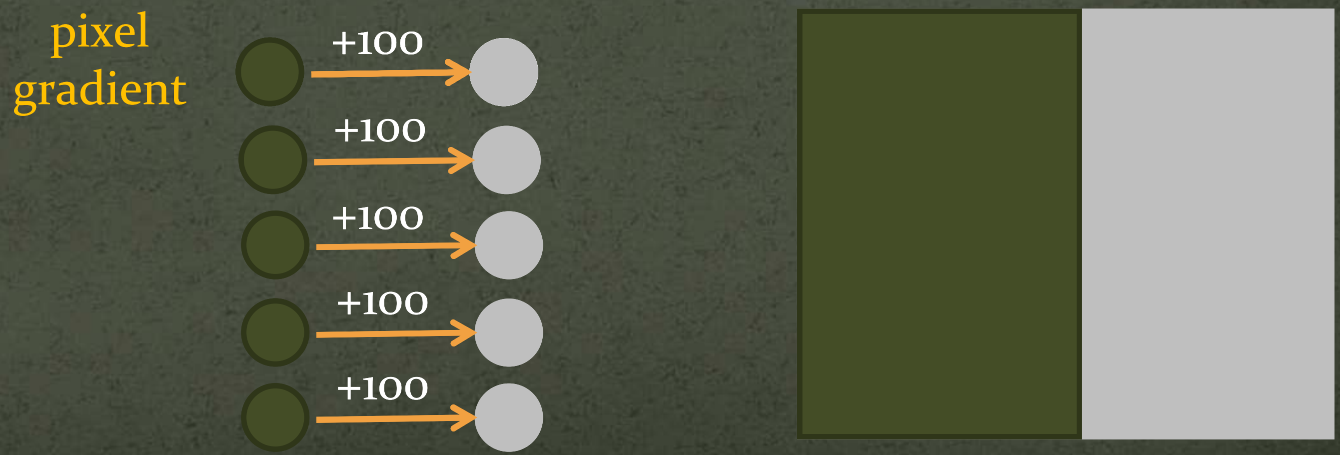
pixel
gradient

Motivation for gradient-domain filtering?

- Can be used to exert high-level control over images
  - gradients – low level image-features
  - gradients – give rise to high level image-features

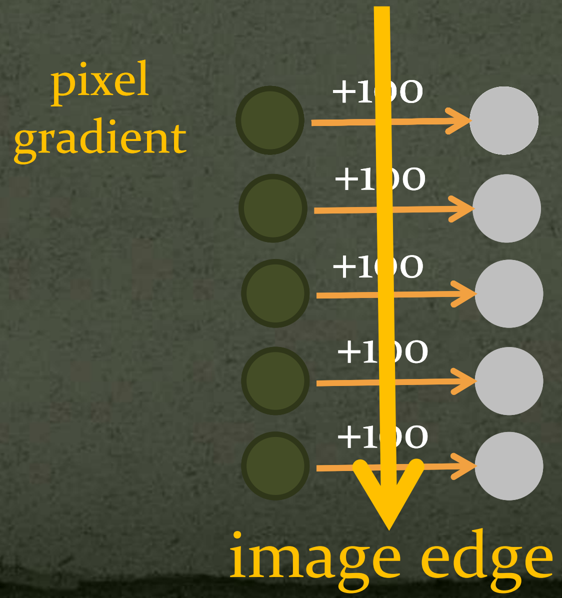
Motivation for gradient-domain filtering?

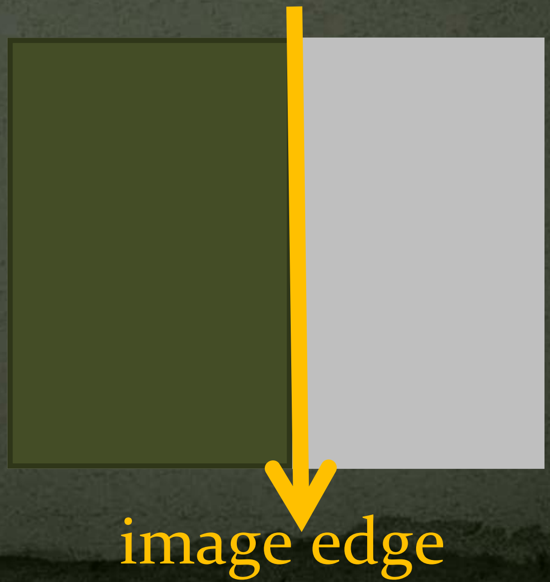
- Can be used to exert high-level control over images
  - gradients – low level image-features
  - gradients – give rise to high level image-features



Motivation for gradient-domain filtering?

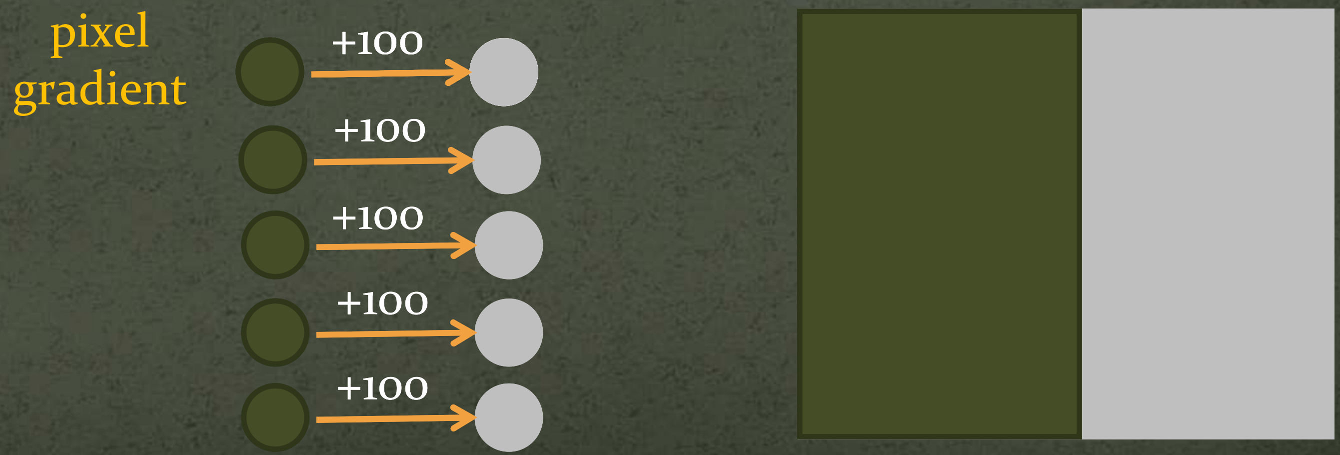
- Can be used to exert high-level control over images
  - gradients – low level image-features
  - gradients – give rise to high level image-features





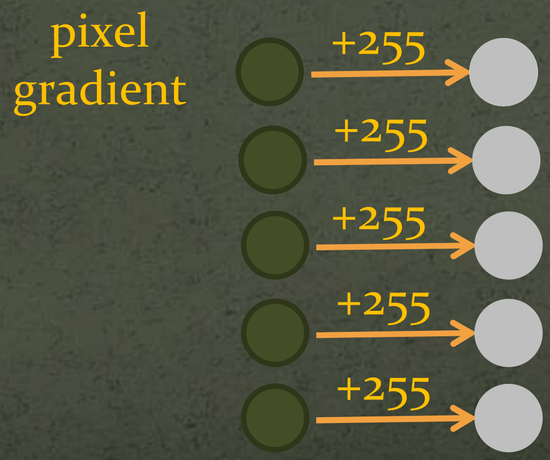
Motivation for gradient-domain filtering?

- Can be used to exert high-level control over images
  - gradients – low level image-features
  - gradients – give rise to high level image-features
  - manipulate local gradients to manipulate global image interpretation



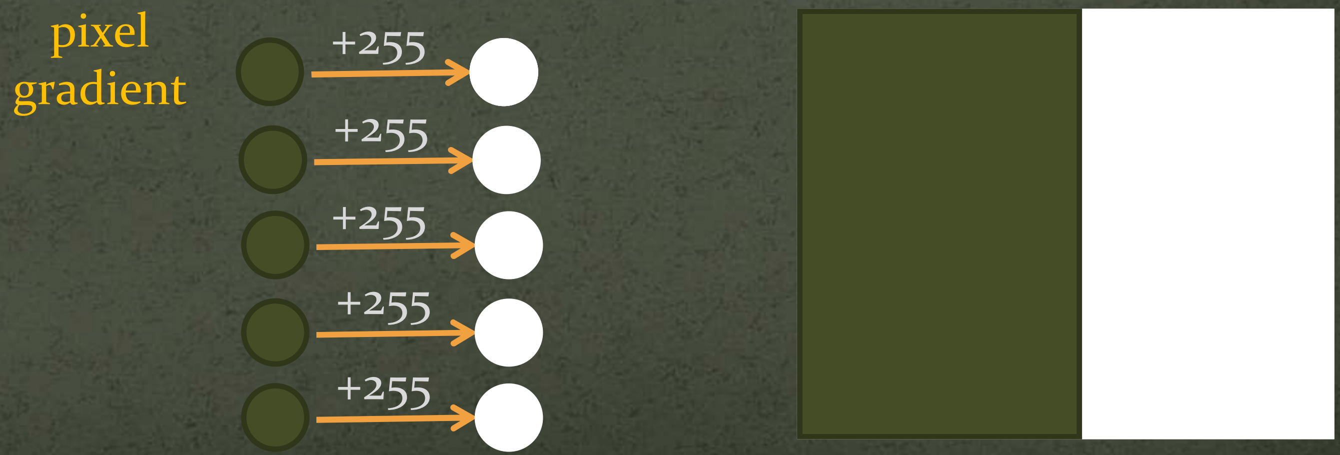
Motivation for gradient-domain filtering?

- Can be used to exert high-level control over images
  - gradients – low level image-features
  - gradients – give rise to high level image-features
  - manipulate local gradients to manipulate global image interpretation



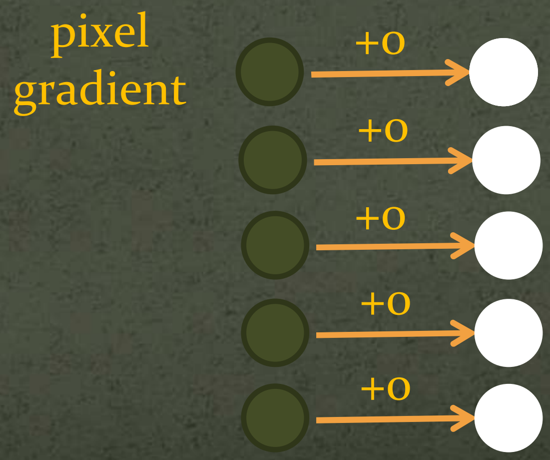
Motivation for gradient-domain filtering?

- Can be used to exert high-level control over images
  - gradients – low level image-features
  - gradients – give rise to high level image-features
  - manipulate local gradients to manipulate global image interpretation



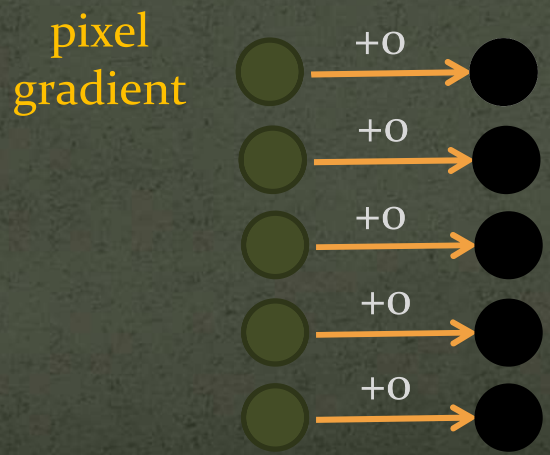
Motivation for gradient-domain filtering?

- Can be used to exert high-level control over images
  - gradients – low level image-features
  - gradients – give rise to high level image-features
  - manipulate local gradients to manipulate global image interpretation



Motivation for gradient-domain filtering?

- Can be used to exert high-level control over images
  - gradients – low level image-features
  - gradients – give rise to high level image-features
  - manipulate local gradients to manipulate global image interpretation



Motivation for gradient-domain filtering?

- Can be used to exert high-level control over images
  - gradients – give rise to high level image-features

Motivation for gradient-domain filtering?

- Can be used to exert
  high-level control over images
  - gradients – give rise to high level image-features
    - Edges

Motivation for gradient-domain filtering?

- Can be used to exert high-level control over images
  - gradients – give rise to high level image-features
    - Edges
      - object boundaries
      - depth discontinuities
      - shadows
      - …

Motivation for gradient-domain filtering?

- Can be used to exert high-level control over images
  - gradients – give rise to high level image-features
    - Edges
    - Texture

Motivation for gradient-domain filtering?

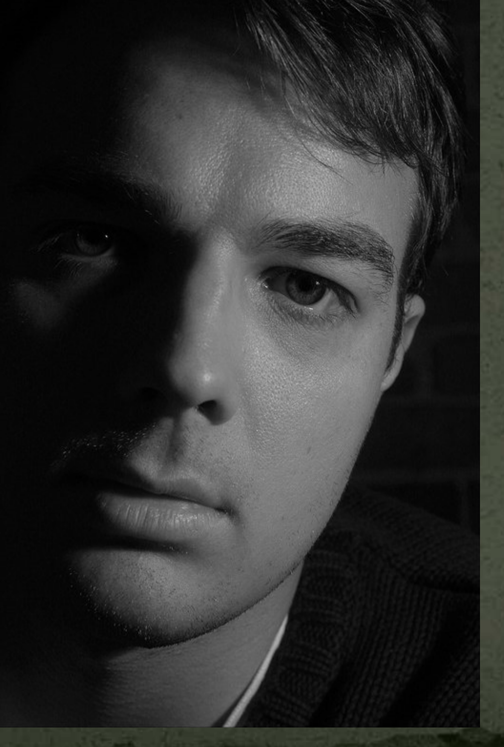
- Can be used to exert high-level control over images
    - gradients – give rise to high level imag
        - Edges
        - Texture
            - visual richness
            - surface properties

Motivation for gradient-domain filtering?

- Can be used to exert high-level control over images
  - gradients – give rise to high level image-features
    - Edges
    - Texture
    - Shading

Motivation for gradient-domain filtering?

- Can be used to exert high-level control over images
  - gradients – give rise to high level image-features
    - Edges
    - Texture
    - Shading
      - lighting



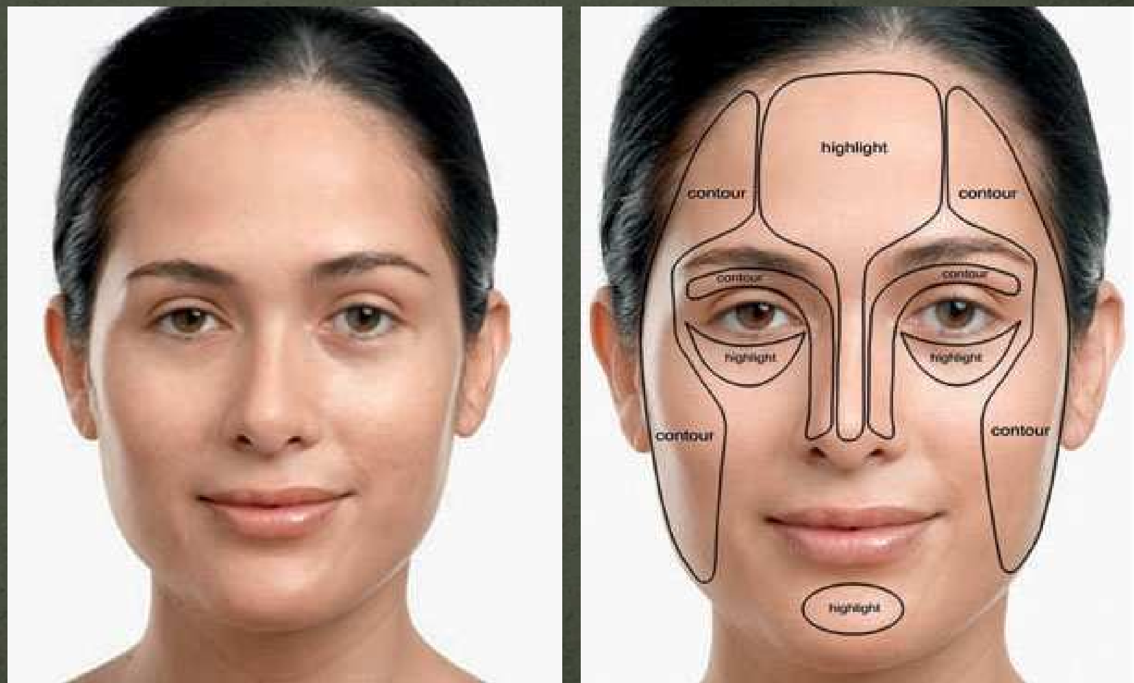
Motivation for gradient-domain filtering?

- Can be used to exert high-level control over images
  - gradients – give rise to high level image-features
    - Edges
    - Texture
    - Shading
      - lighting
      - shape

sculpting the face
using shading (makeup)

Motivation for gradient-domain filtering?

- Can be used to exert high-level control over images
  - gradients – give rise to high level image-features
    - Edges
    - Texture
    - Shading
      - lighting
      - shape



sculpting the face
using shading (makeup)

Motivation for gradient-domain filtering?

- Can be used to exert high-level control over images
  - gradients – give rise to high level image-features
    - Edges
    - Texture
    - Shading
      - lighting
      - shape

sculpting the face
using shading (makeup)

Motivation for gradient-domain filtering?

- Can be used to exert high-level control over images
  - gradients – give rise to high level image-features
    - Edges
    - Texture
    - Shading
      - lighting
      - shape

sculpting the face
using shading (makeup)

Motivation for gradient-domain filtering?

- Can be used to exert high-level control over images
  - gradients – give rise to high level image-features
    - Edges
    - Texture
    - Shading

Motivation for gradient-domain filtering?

- Can be used to exert high-level control over images
  - gradients – give rise to high level image-features
    - Edges
    - Texture
    - Shading
    - Artifacts

Motivation for gradient-domain filtering?

- Can be used to exert high-level control over images
  - gradients – give rise to high level image-features
    - Edges
    - Texture
    - Shading
    - Artifacts
      - noise

sensor noise

Motivation for gradient-domain filtering?

- Can be used to exert high-level control over images
  - gradients – give rise to high level image-features
    - Edges
    - Texture
    - Shading
    - Artifacts
      - noise
      - seams

seams in composite images

Motivation for gradient-domain filtering?

- Can be used to exert high-level control over images
  - gradients – give rise to high level image-features
    - Edges
    - Texture
    - Shading
    - Artifacts
      - noise
      - seams
      - compression artifacts

blocking in compressed images

Motivation for gradient-domain filtering?

- Can be used to exert high-level control over images
  - gradients – give rise to high level image-features
    - Edges
    - Texture
    - Shading
    - Artifacts
      - noise
      - seams
      - compression artifacts

ringing in compressed images

Motivation for gradient-domain filtering?

- Can be used to exert high-level control over images

GradientShop

- Optimization framework

Pravin Bhat et al

GradientShop

- Optimization framework
  - Input unfiltered image – u

GradientShop

- Optimization framework
  - Input unfiltered image – ***u***
  - Output filtered image – ***f***

GradientShop

- Optimization framework
  - Input unfiltered image – ***u***
  - Output filtered image – ***f***
  - Specify desired pixel-differences – (g^x, g^y)

Energy function

$$\boxed{\min_{f} \quad (f_x - g^x)^2 + \quad (f_y - g^y)^2}$$

GradientShop

- Optimization framework
  - Input unfiltered image – $\boldsymbol{u}$
  - Output filtered image – $\boldsymbol{f}$
  - Specify desired pixel-differences – $(\boldsymbol{g}^x, \boldsymbol{g}^y)$
  - Specify desired pixel-values – $\boldsymbol{d}$

Energy function

$$\boxed{\min_{f} \quad (f_x - g^x)^2 + \quad (f_y - g^y)^2 + \quad (f - d)^2}$$

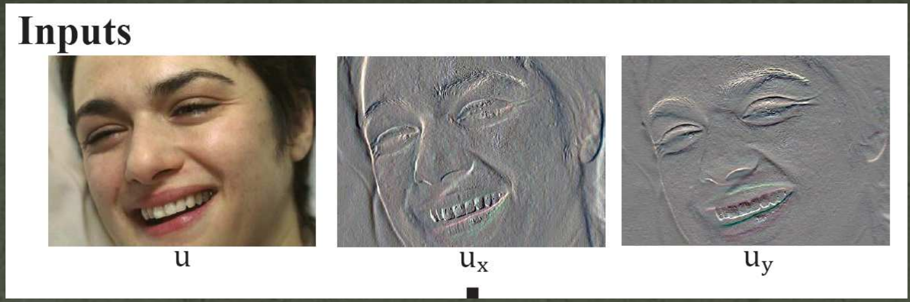
GradientShop

- Optimization framework
  - Input unfiltered image – $\boldsymbol{u}$
  - Output filtered image – $\boldsymbol{f}$
  - Specify desired pixel-differences – $(\boldsymbol{g}^x, \boldsymbol{g}^y)$
  - Specify desired pixel-values – $\boldsymbol{d}$
  - Specify constraints weights – $(\boldsymbol{w}^x, \boldsymbol{w}^y, \boldsymbol{w}^d)$

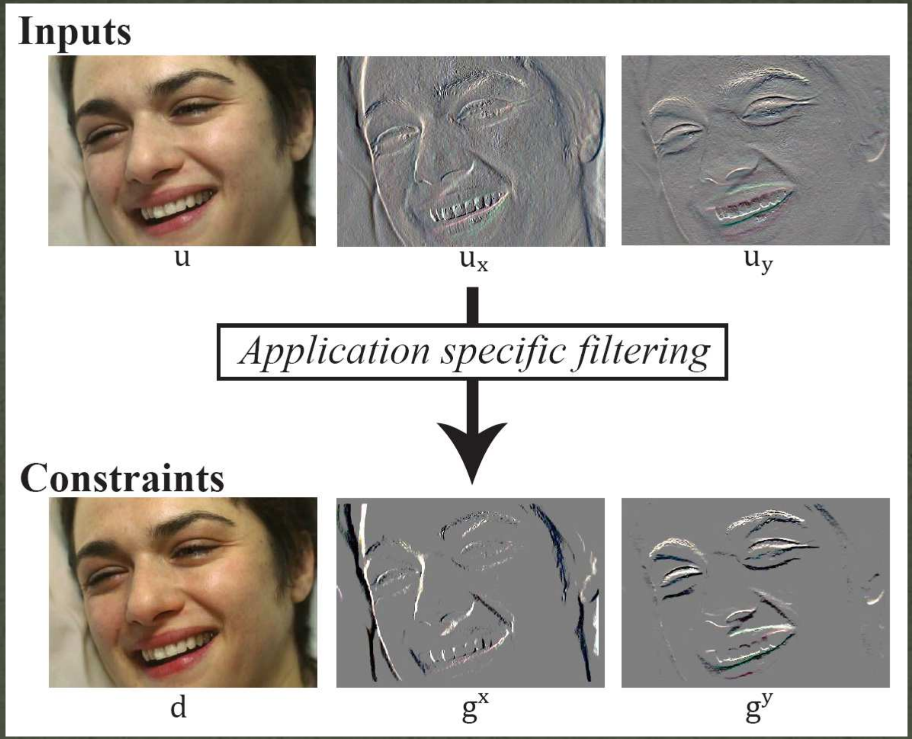
Energy function

$$\boxed{\min_{f} \quad \boldsymbol{w}^x(\boldsymbol{f}_x - \boldsymbol{g}^x)^2 + \boldsymbol{w}^y(\boldsymbol{f}_y - \boldsymbol{g}^y)^2 + \boldsymbol{w}^d(\boldsymbol{f} - \boldsymbol{d})^2}$$

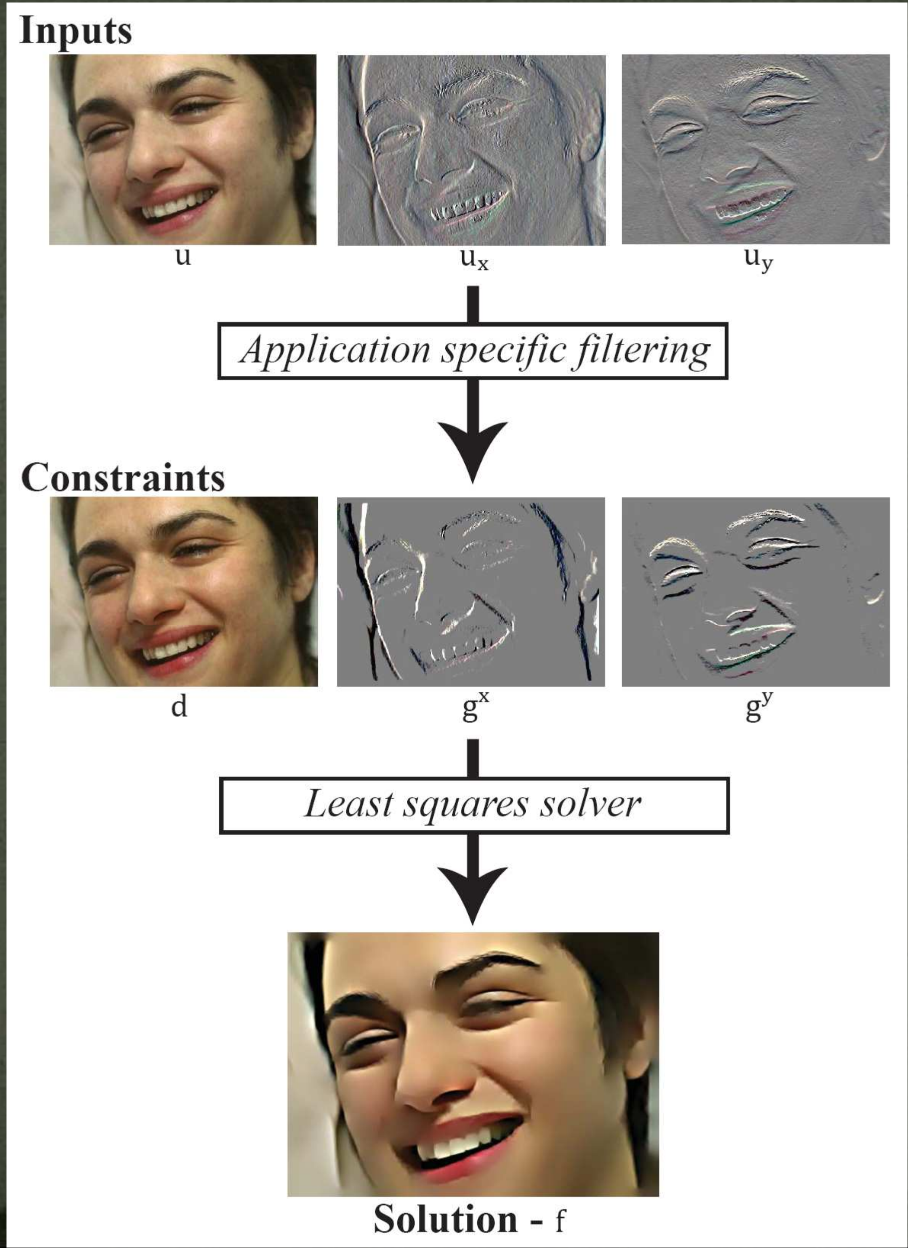
GradientShop



GradientShop



GradientShop



Pseudo image relighting

- change scene illumination in post-production
- example

input

Pseudo image relighting

- change scene illumination in post-production
- example

manual relight

Pseudo image relighting

- change scene illumination
  in post-production
- example

input

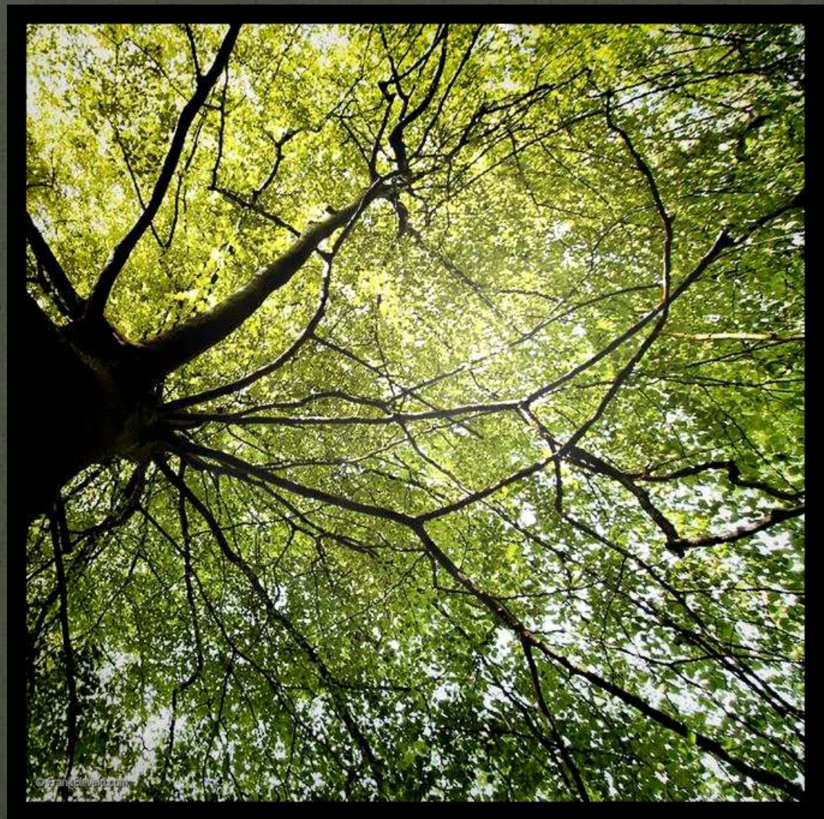
Pseudo image relighting

- change scene illumination
  in post-production
- example

GradientShop relight

Pseudo image relighting

- change scene illumination
  in post-production
- example



GradientShop relight

Pseudo image relighting

- change scene illumination in post-production
- example

GradientShop relight

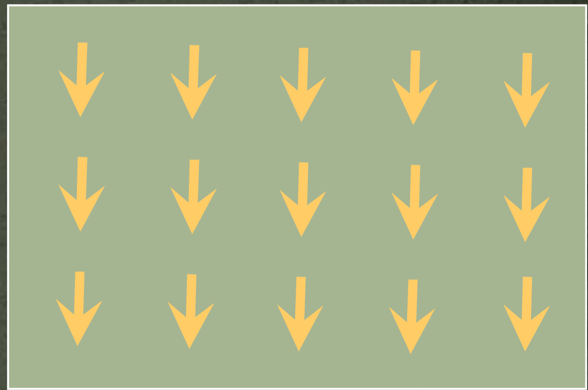
Pseudo image relighting

- change scene illumination in post-production
- example

GradientShop relight

Pseudo image relighting

u



o

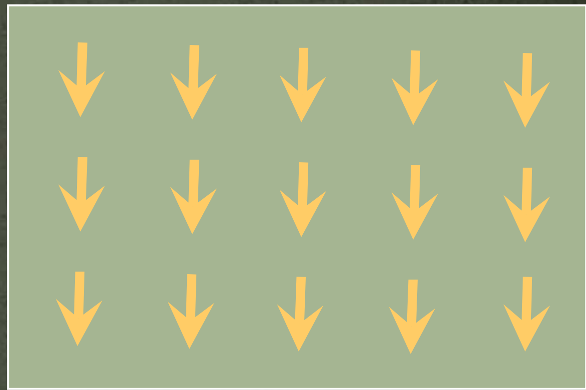
f

Pseudo image relighting

Energy function

$$\min_{f} \; w^x(f_x - g^x)^2 + w^y(f_y - g^y)^2 + w^d(f - d)^2$$

u



o

f

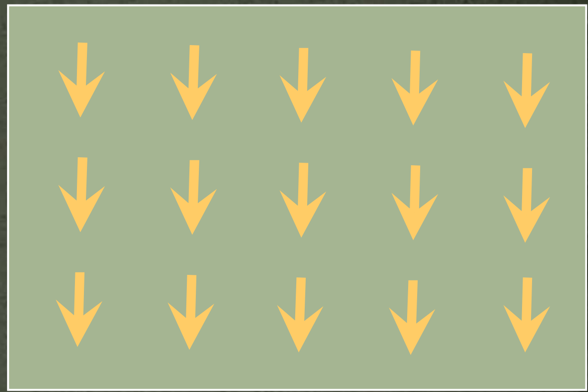
Pseudo image relighting

Energy function

$$\boxed{\min_{f} \; w^x(f_x - g^x)^2 + w^y(f_y - g^y)^2 + w^d(f - d)^2}$$

- Definition:
  - $d = u$

u



o

f

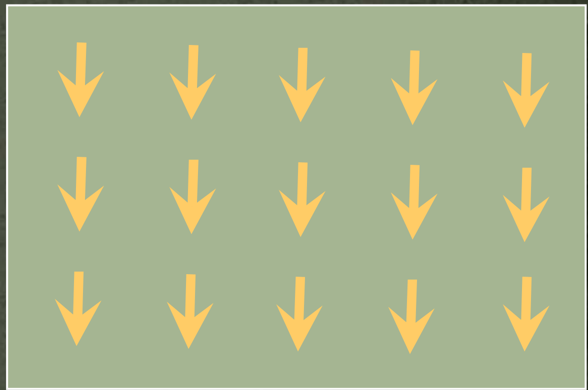
Pseudo image relighting

Energy function

$$\min_{f} \; w^x(f_x - g^x)^2 + w^y(f_y - g^y)^2 + w^d(f - d)^2$$

- Definition:
  - $d = u$
  - $g^x(p) = u_x(p) * (1 + a(p))$
  - $a(p) = \max(0, -\nabla u(p).o(p))$

u



o

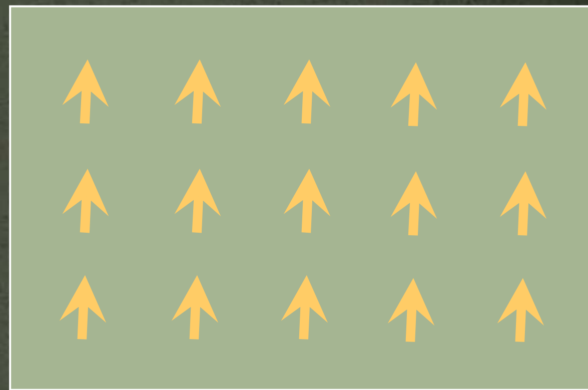
f

Pseudo image relighting

Energy function

$$\min_f \; w^x(f_x - g^x)^2 + w^y(f_y - g^y)^2 + w^d(f - d)^2$$

u



o

- Definition:
  - $d = u$
  - $g^x(p) = u_x(p) * (1 + a(p))$
  - $a(p) = \max(0, -\nabla u(p).o(p))$

f

Sparse data interpolation

- Interpolate scattered data
  over images/video

Sparse data interpolation

- Interpolate scattered data over images/video
- Example app: Colorization*

input

output

*Levin et al. – SIGRAPH 2004

Sparse data interpolation

u

user data

f

Sparse data interpolation

Energy function

$$\boxed{\min_{f} \; w^x (f_x - g^x)^2 + w^y (f_y - g^y)^2 + w^d (f - d)^2}$$

u

user data

f

Sparse data interpolation

Energy function

$$\min_{f} \; w^x(f_x - g^x)^2 + w^y(f_y - g^y)^2 + w^d(f - d)^2$$

- Definition:
  - d = user_data

u

user data

f

Sparse data interpolation

Energy function

$$\boxed{\min_{f} \quad w^x(f_x - g^x)^2 + w^y(f_y - g^y)^2 + w^d(f - d)^2}$$

- Definition:
  - d = user_data
  - **if user_data(p) defined**
    $w^d(p) = 1$
    else
    $w^d(p) = 0$

u

user data

f

Sparse data interpolation

Energy function

$$\min_f \; w^x(f_x - g^x)^2 + w^y(f_y - g^y)^2 + w^d(f - d)^2$$

- Definition:
  - d = user_data
  - if user_data(p) defined
    $w^d(p) = 1$
    else
    $w^d(p) = 0$
  - $g^x(p) = 0$; $g^y(p) = 0$

u

user data

f

Sparse data interpolation

Energy function

$$\boxed{\min_f \; w^x(f_x - g^x)^2 + w^y(f_y - g^y)^2 + w^d(f - d)^2}$$

u

user data

- Definition:
  - d = user_data
  - if user_data(p) defined
    $w^d(p) = 1$
    else
    $w^d(p) = 0$
  - $g^x(p) = 0$; $g^y(p) = 0$
  - $w^x(p) = 1/(1 + c^*|u_x(p)|)$
    $w^y(p) = 1/(1 + c^*|u_y(p)|)$

f

Sparse data interpolation

Energy function

$$\boxed{\min_{f} \; w^x(f_x - g^x)^2 + w^y(f_y - g^y)^2 + w^d(f - d)^2}$$

- Definition:
  - d = user_data
  - if user_data(p) defined
    $w^d(p) = 1$
    else
    $w^d(p) = 0$
  - $g^x(p) = 0$; $g^y(p) = 0$
  - $w^x(p) = 1/(1 + c^*|u_x(p)|)$
    $w^y(p) = 1/(1 + c^*|u_y(p)|)$

u

user data

f

Sparse data interpolation

Energy function

$$\min_f \; w^x(f_x - g^x)^2 + w^y(f_y - g^y)^2 + w^d(f - d)^2$$

- Definition:
  - d = user_data
  - if user_data(p) defined
    $w^d(p) = 1$
    else
    $w^d(p) = 0$
  - $g^x(p) = 0$; $g^y(p) = 0$
  - $w^x(p) = 1/(1 + c^*|e^l(p)|)$
    $w^y(p) = 1/(1 + c^*|e^l(p)|)$

u

user data

f