Image Blending and Compositing

CS194: Image Manipulation & Computational Photography
Alexei Efros, UC Berkeley, Fall 2014

Image Compositing

Compositing Procedure

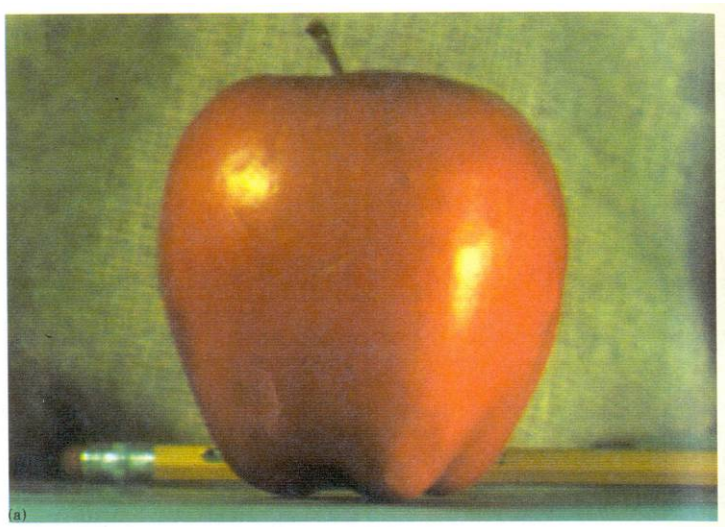
1. Extract Sprites (e.g using *Intelligent Scissors* in Photoshop)

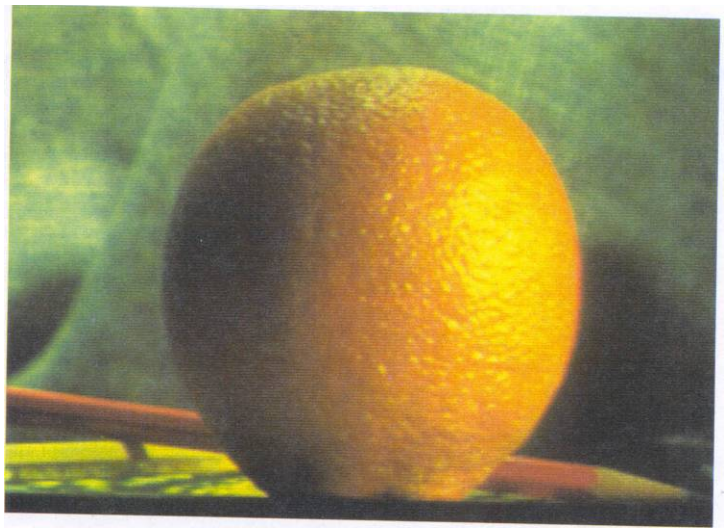


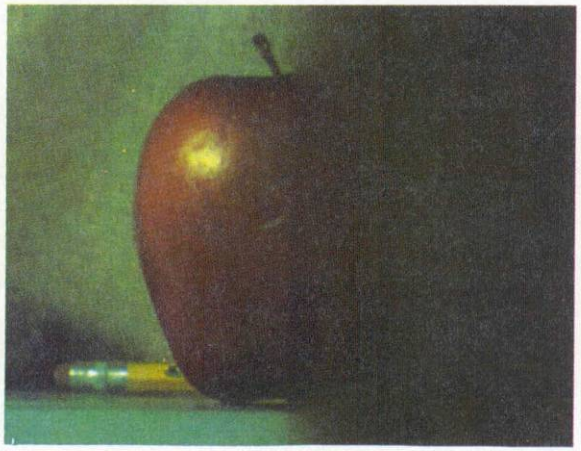
2. Blend them into the composite (in the right order)

Composite by
David Dewey

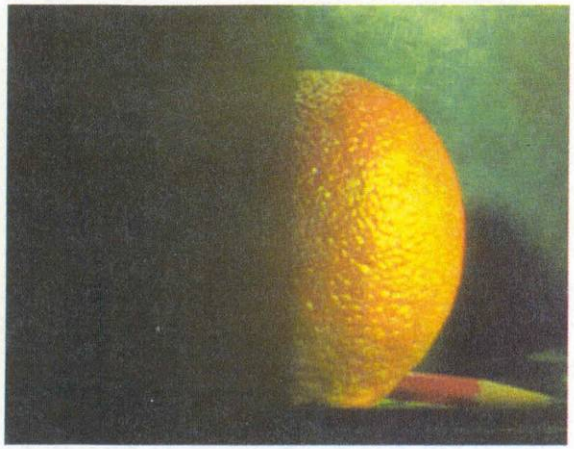
Pyramid Blending



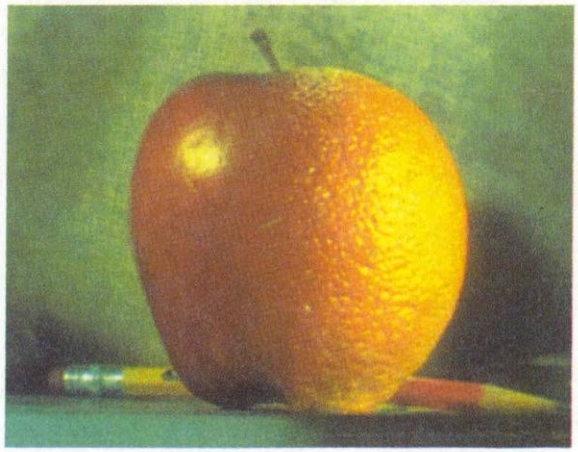




(d)



(h)



(l)

Gradient Domain vs. Frequency Domain

In Pyramid Blending, we decomposed our images into several frequency bands, and transferred them separately

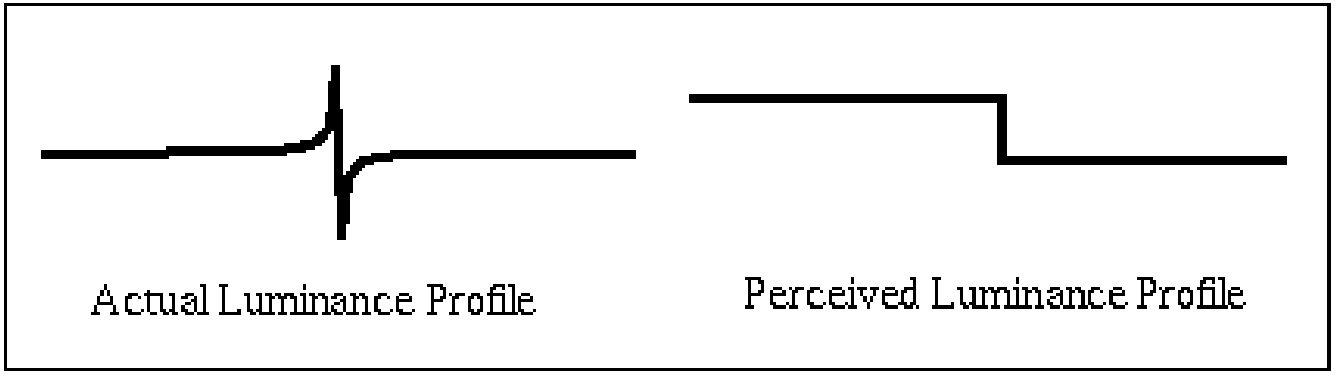
- But boundaries appear across multiple bands

But what representation based on 1st derivatives (gradients) of the image?:

- Represents local change (across all frequences)
- No need for low-res image
  - captures everything (up to a constant)
- Blending/Editing in Gradient Domain:
  - Differentiate
  - Blend / edit / whatever
  - Reintegrate

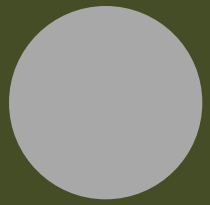
Gradients vs. Pixels

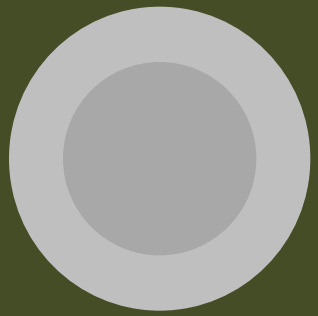
Craik-O'Brien Cornsweet Effect

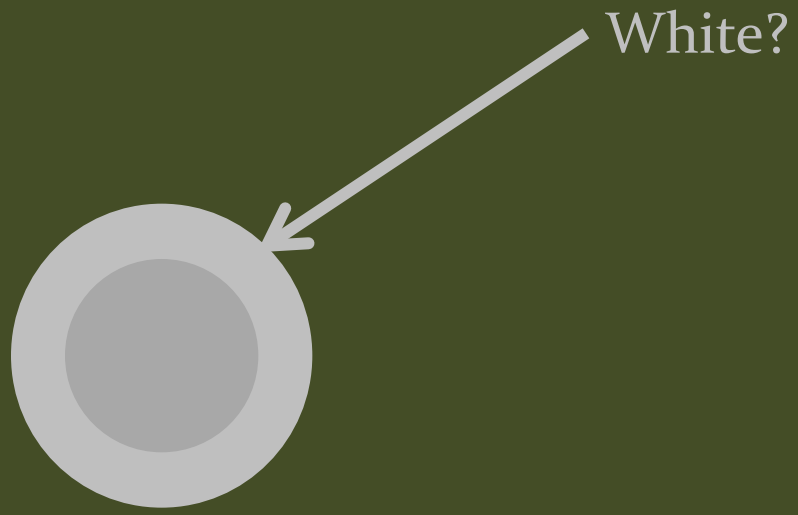


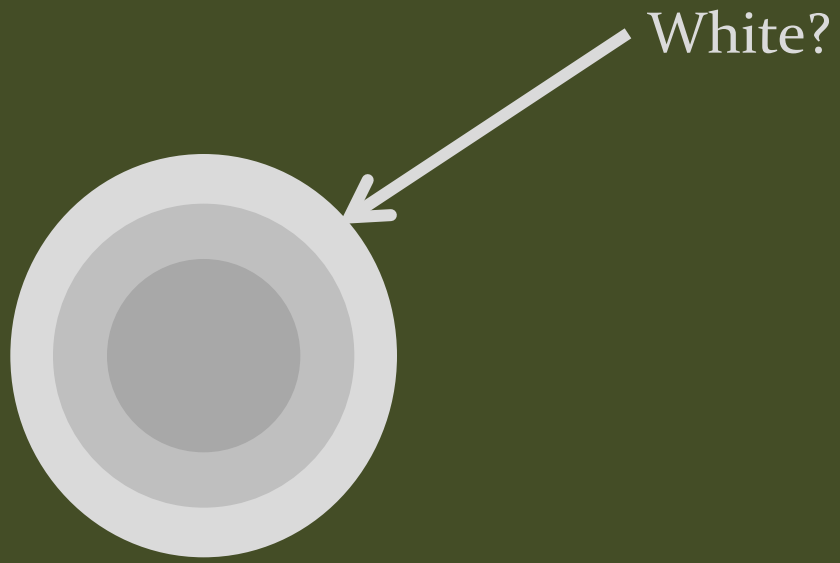
Gilchrist Illusion

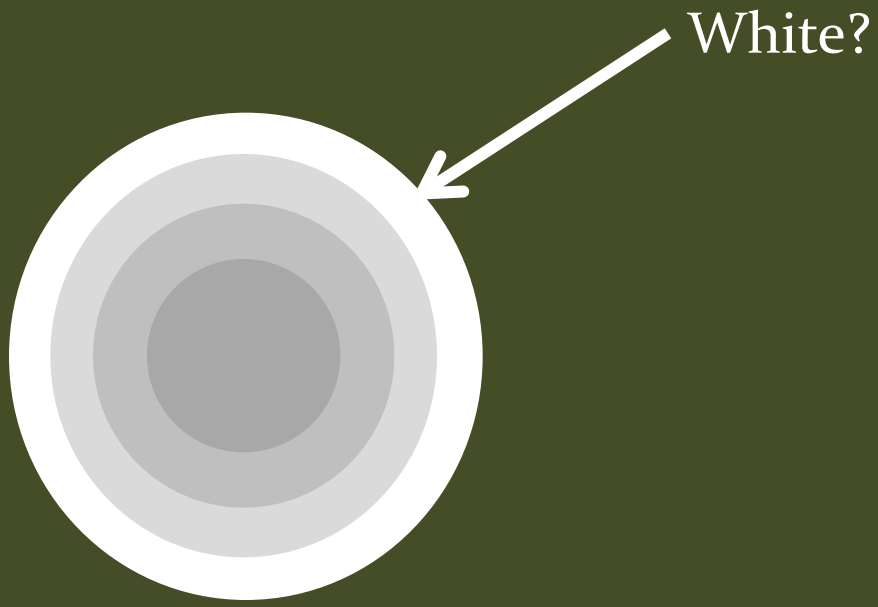
(c.f. Exploratorium)

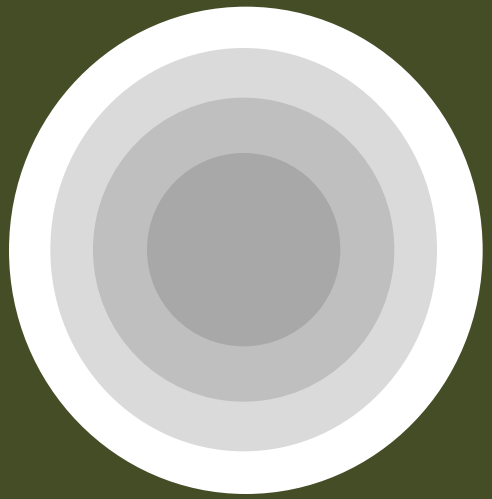




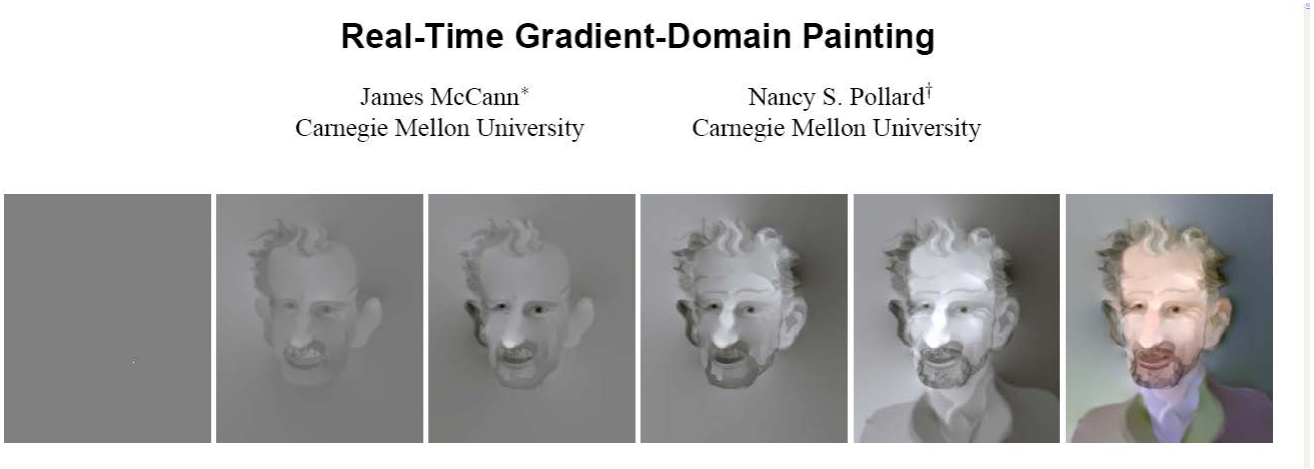

White?


White?


White?



Drawing in Gradient Domain



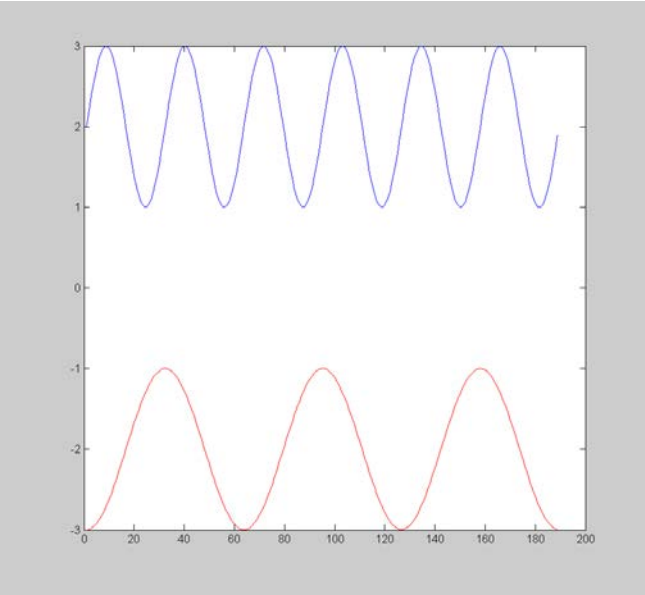
James McCann & Nancy Pollard
Real-Time Gradient-Domain Painting, SIGGRAPH 2009

(paper came out of this class!)

http://www.youtube.com/watch?v=RvhkAfrA0-w&feature=youtu.be

Gradient Domain blending (1D)

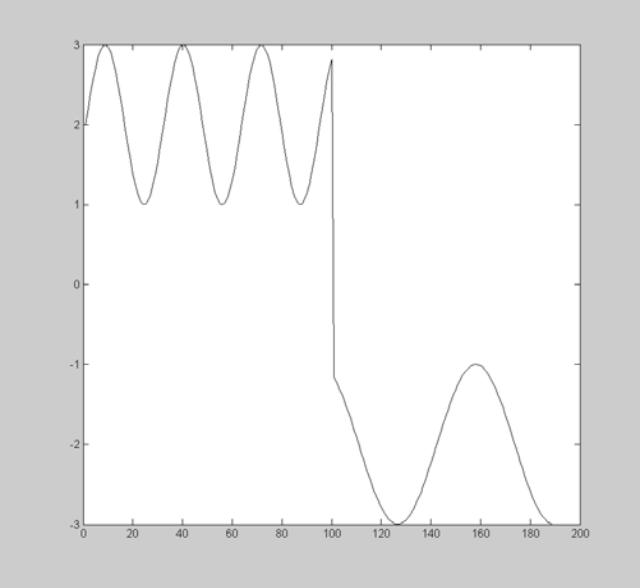
Two signals

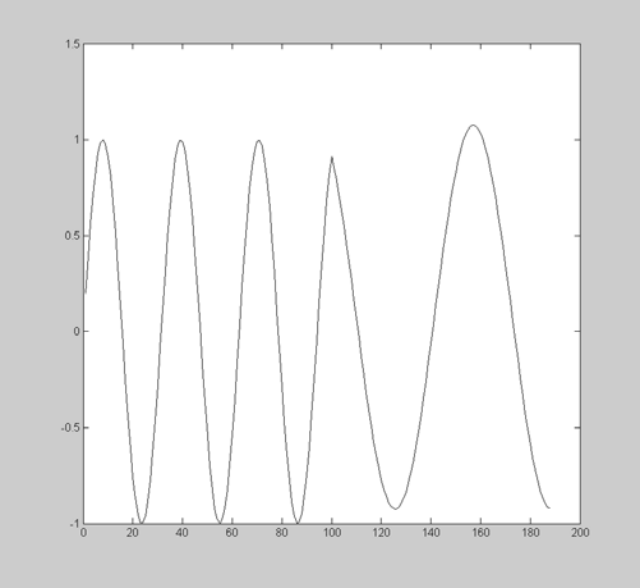


bright

dark

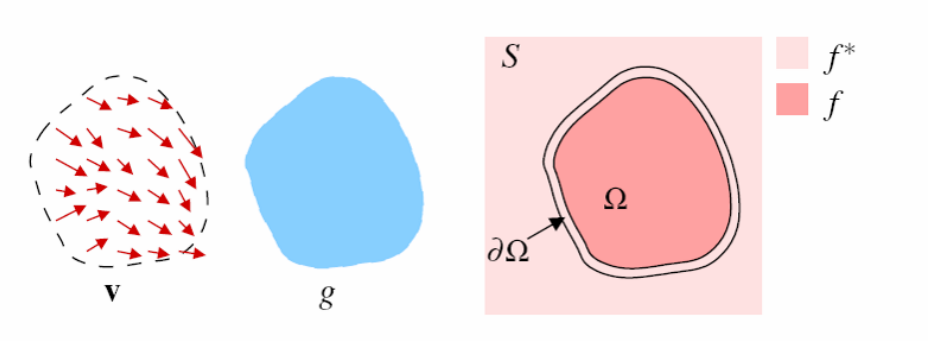
Regular blending





Blending derivatives

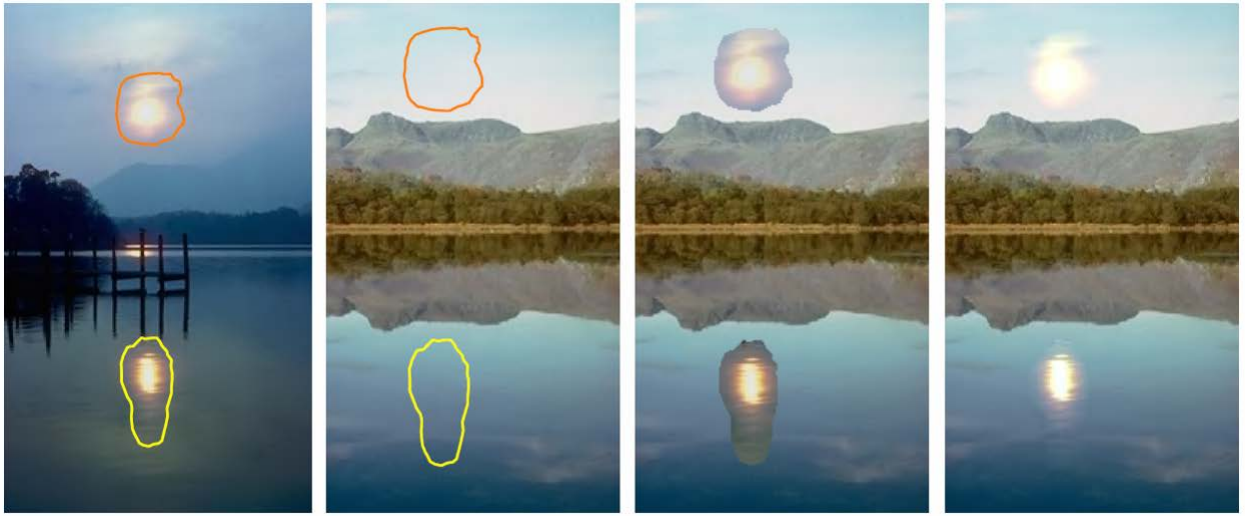
Gradient Domain Blending (2D)



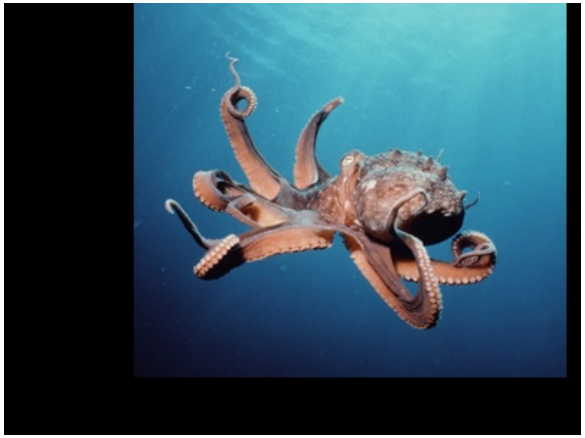
Trickier in 2D:

- 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 (\ in Matlab)

Perez et al., 2003

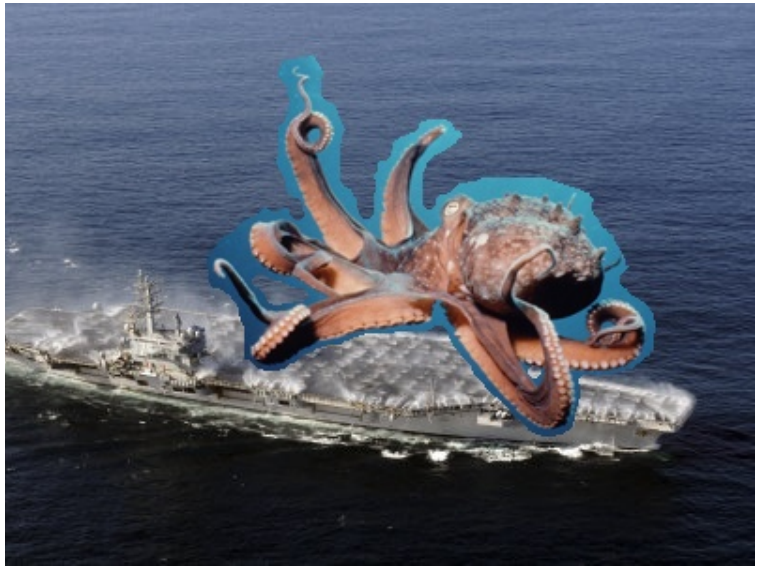


target

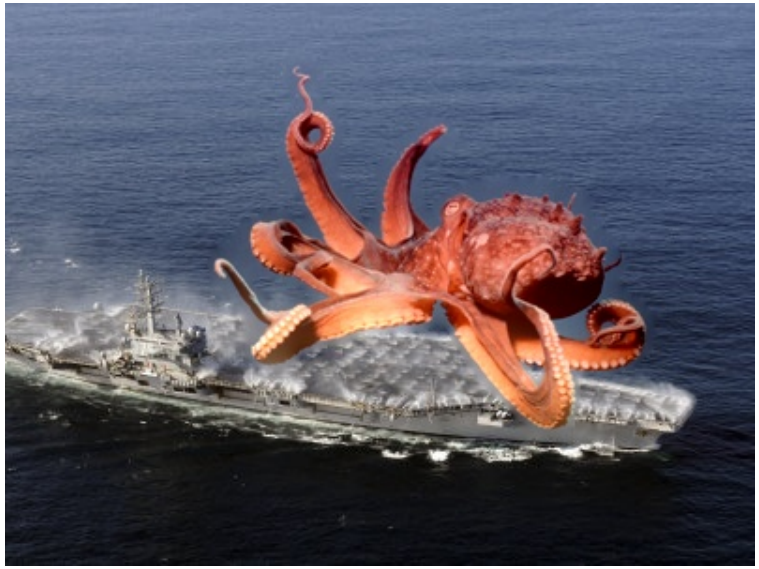


source

mask



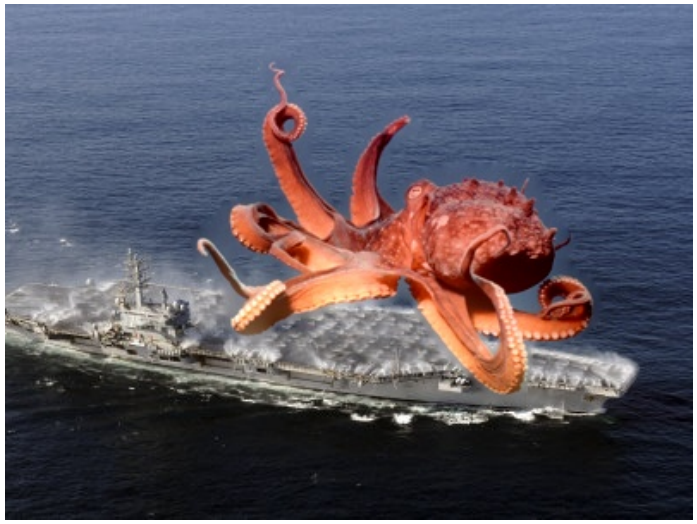
no blending



gradient domain blending

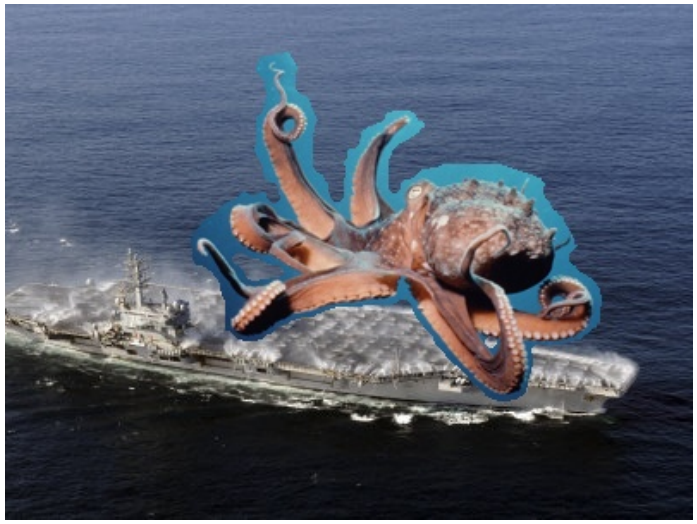
Slide by Mr. Hays

What's the difference?



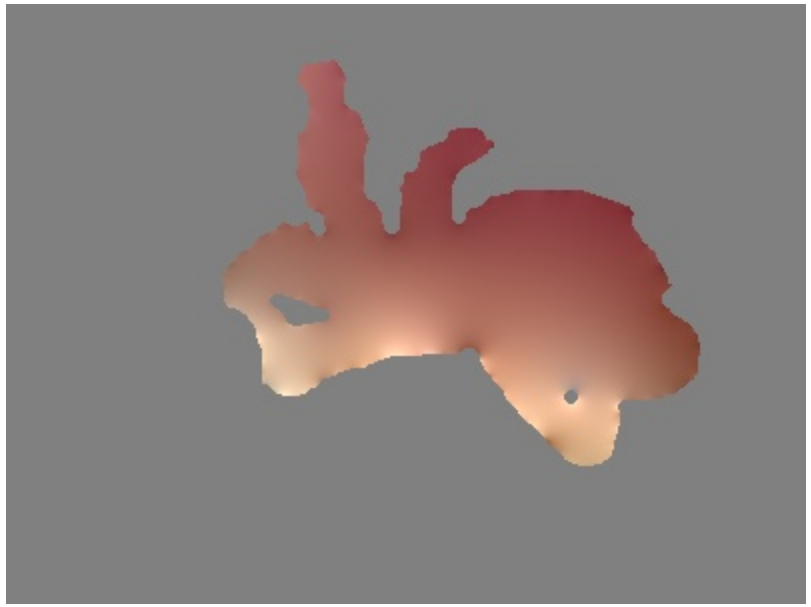
gradient domain blending

-



no blending

=



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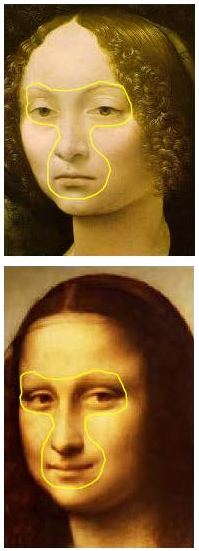
Perez et al, 2003



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

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

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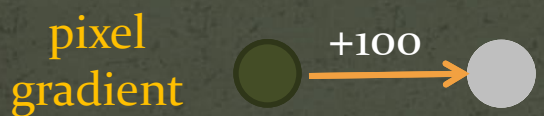

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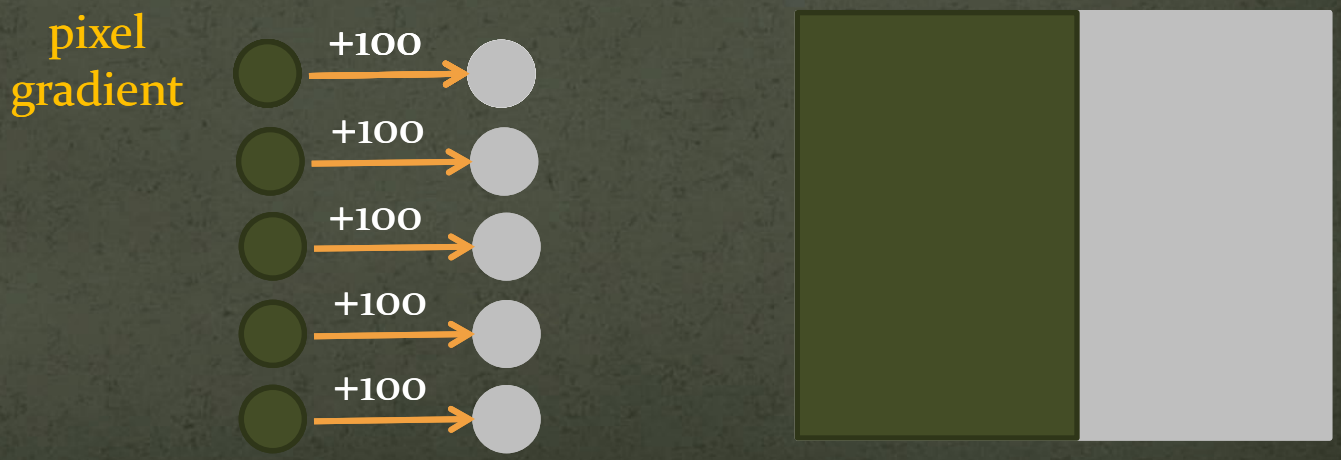

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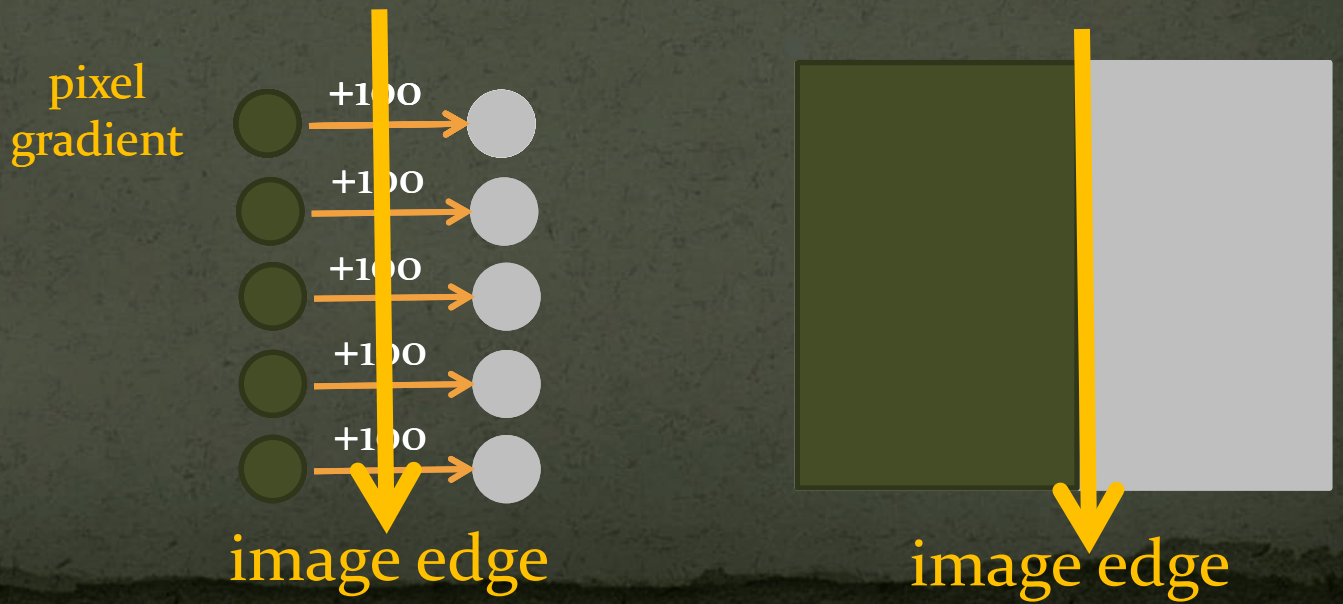

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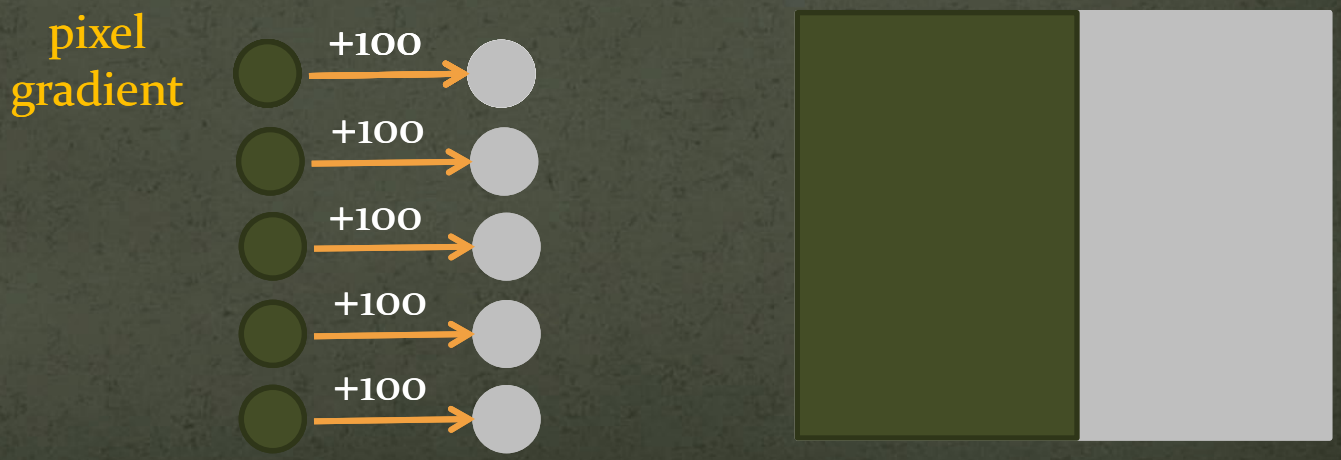
  - manipulate local gradients to manipulate global image interpretation



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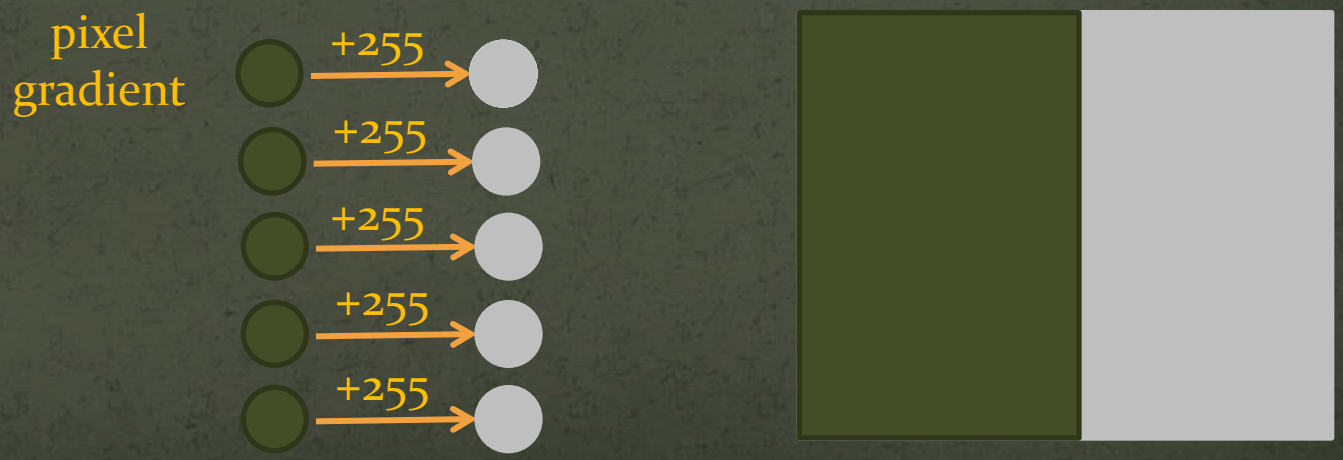

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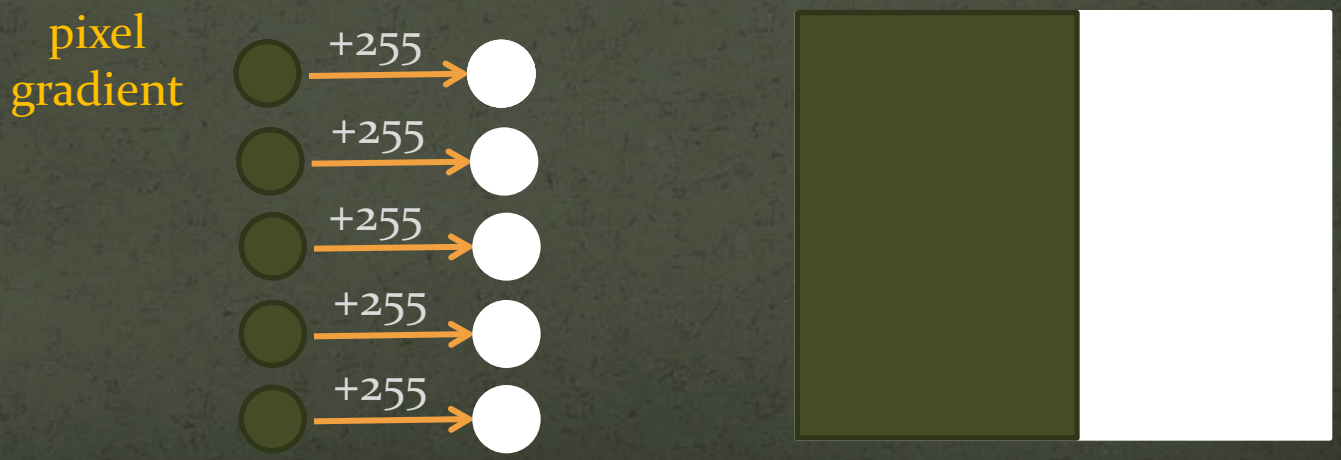

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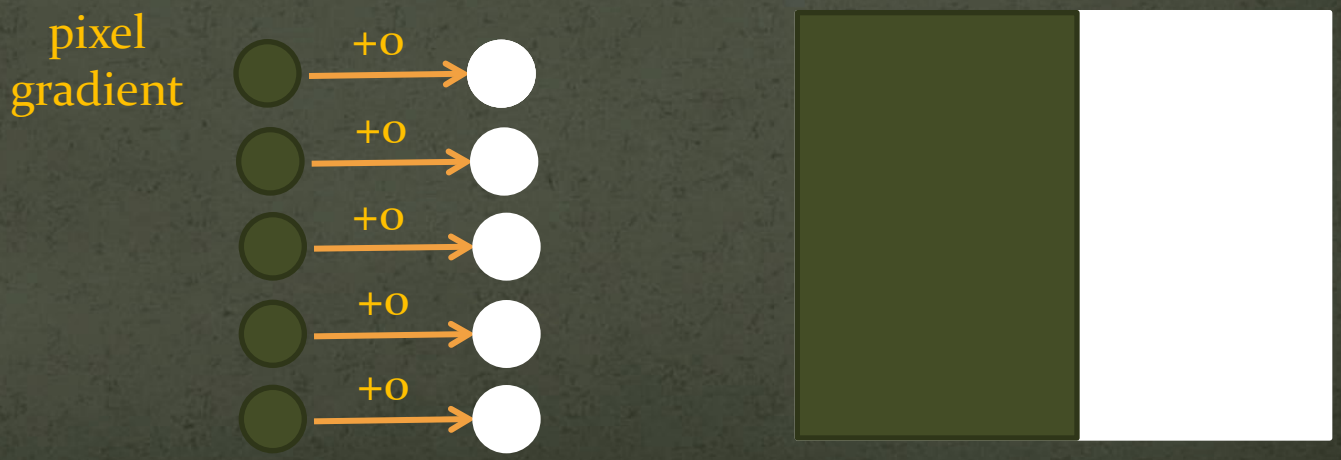

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GradientShop

- 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 – $\boldsymbol{u}$
  - Output filtered image – $\boldsymbol{f}$
  - Specify desired pixel-differences – $(\boldsymbol{g^x}, \boldsymbol{g^y})$

Energy function

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

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

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

GradientShop

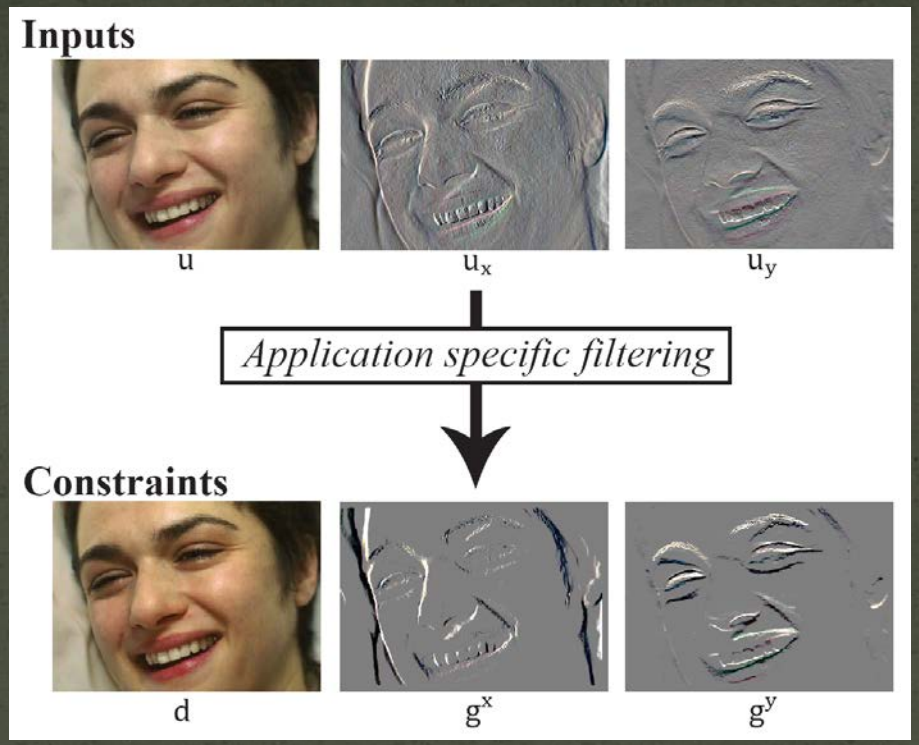
- Optimization framework
  - Input unfiltered image – $\boldsymbol{u}$
  - Output filtered image – $\boldsymbol{f}$
  - Specify desired pixel-differences – $(\boldsymbol{g^x}, \boldsymbol{g^y})$
  - Specify desired pixel-values – $\boldsymbol{d}$
  - Specify constraints weights – $(\boldsymbol{w^x},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

Energy function

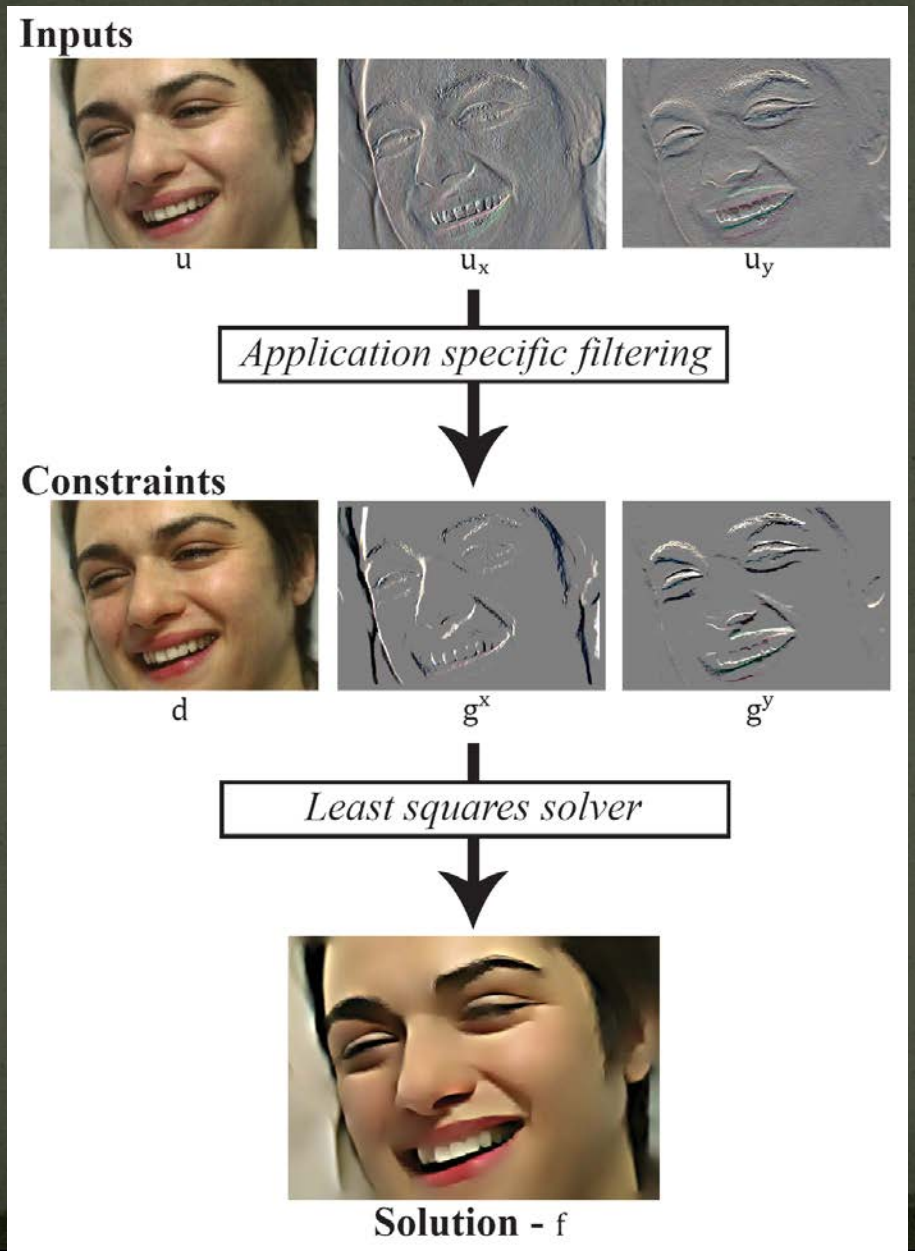
$$\min_{f} \; \boldsymbol{w^x}(\boldsymbol{f_x} - \boldsymbol{g^x})^2 + \boldsymbol{w^y}(\boldsymbol{f_y} - \boldsymbol{g^y})^2 + \boldsymbol{w^d}(\boldsymbol{f} - \boldsymbol{d})^2$$

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

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- example

input

Pseudo image relighting

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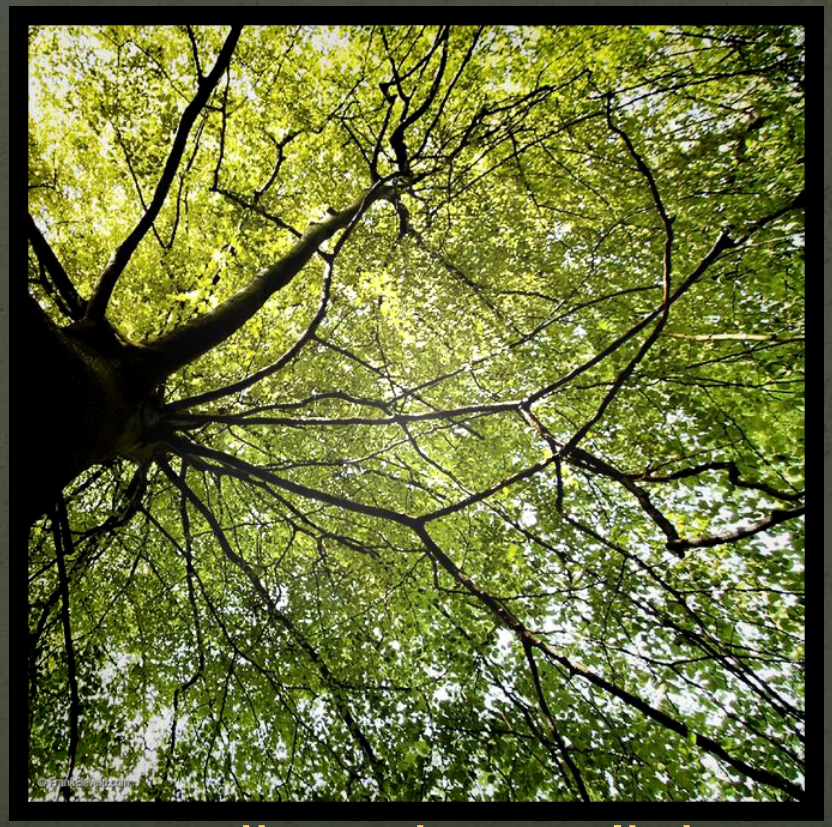

GradientShop relight

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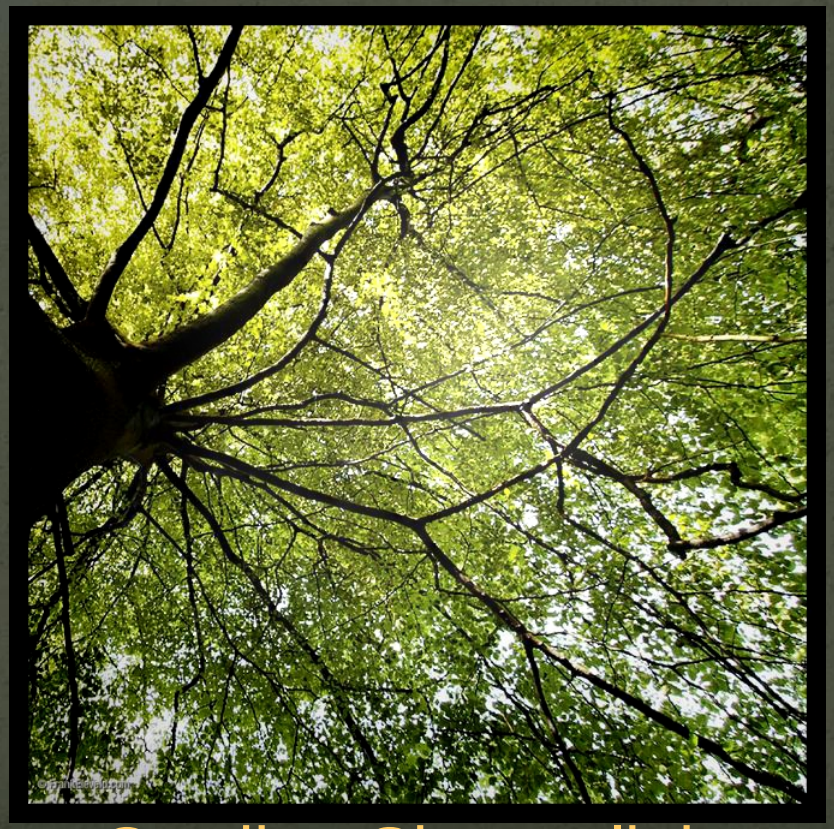

GradientShop relight

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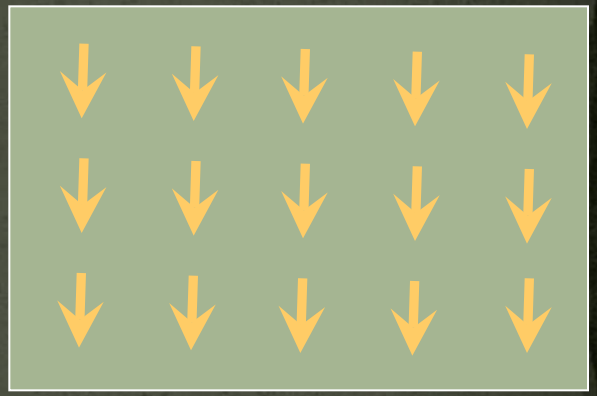
GradientShop relight

Pseudo image relighting

u



o

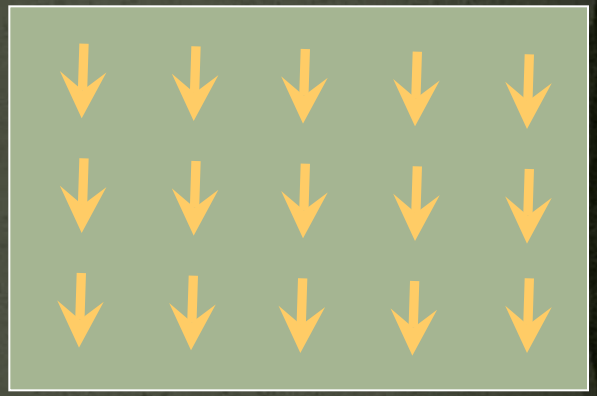
f

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



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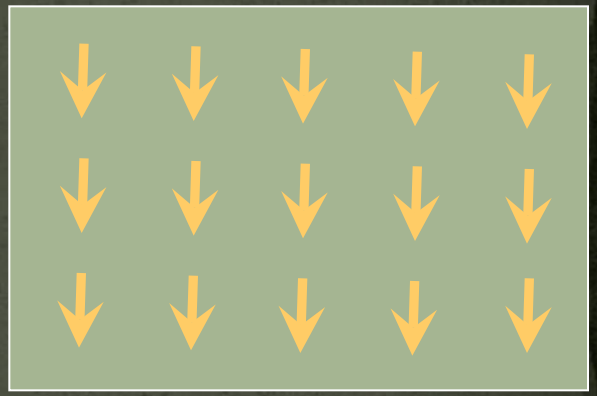
- Definition:
  - $d = u$

u



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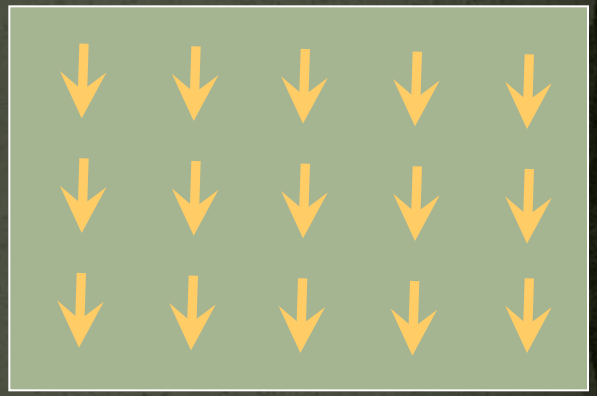

o

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

f

Pseudo image relighting

Energy function

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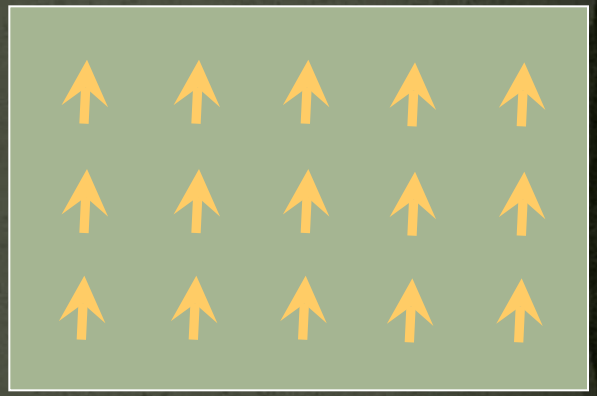

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f

Sparse data interpolation

- Interpolate scattered data over images/video

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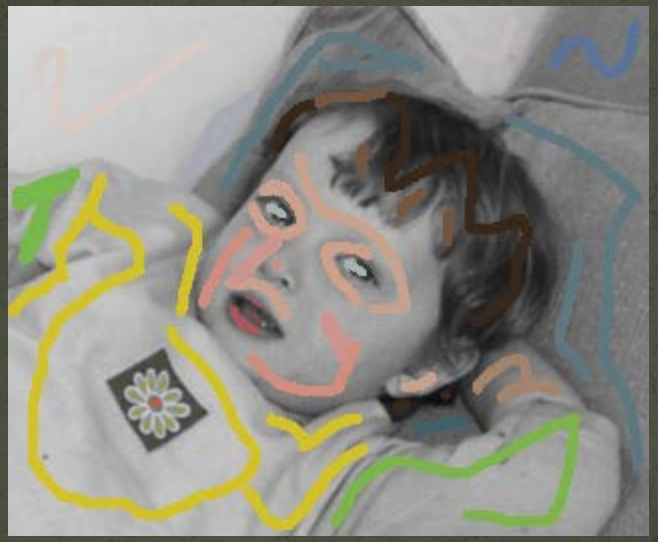
- Example app: Colorization*



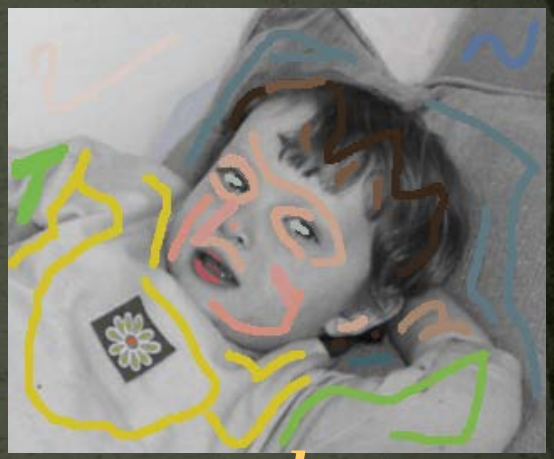
input

output

*Levin et al. – SIGRAPH 2004

Sparse data interpolation

u



user data

f

Sparse data interpolation

Energy function

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

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

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

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

u

user data

f

Sparse data interpolation

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user data

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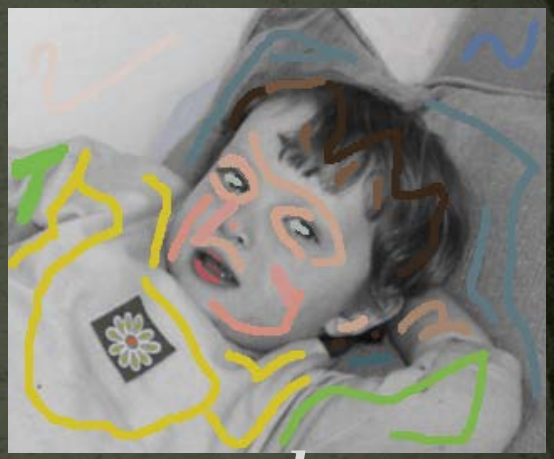
u



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

Don’t blend, CUT!

Moving objects become ghosts

So far we only tried to blend between two images.

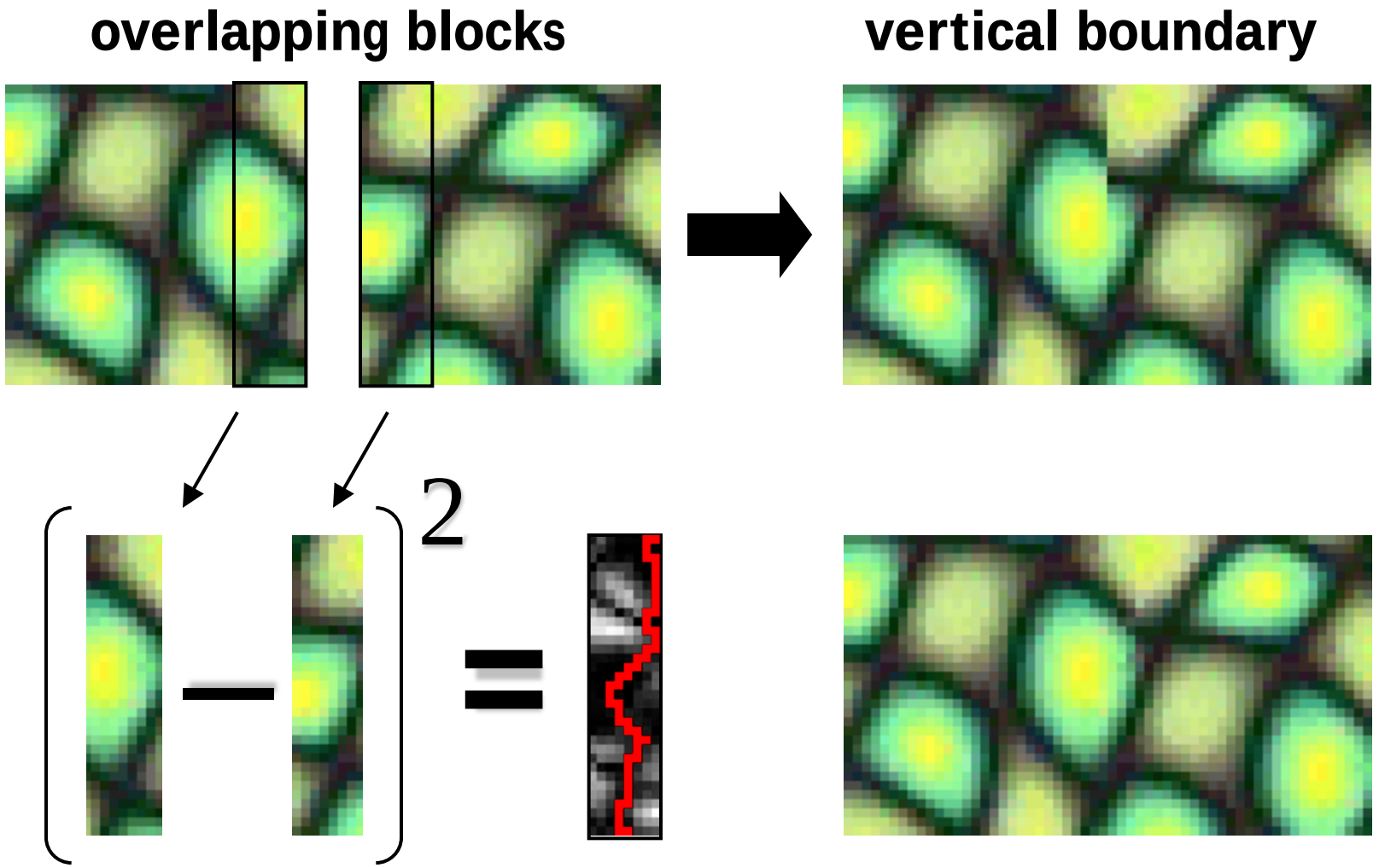
What about finding an optimal seam?

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

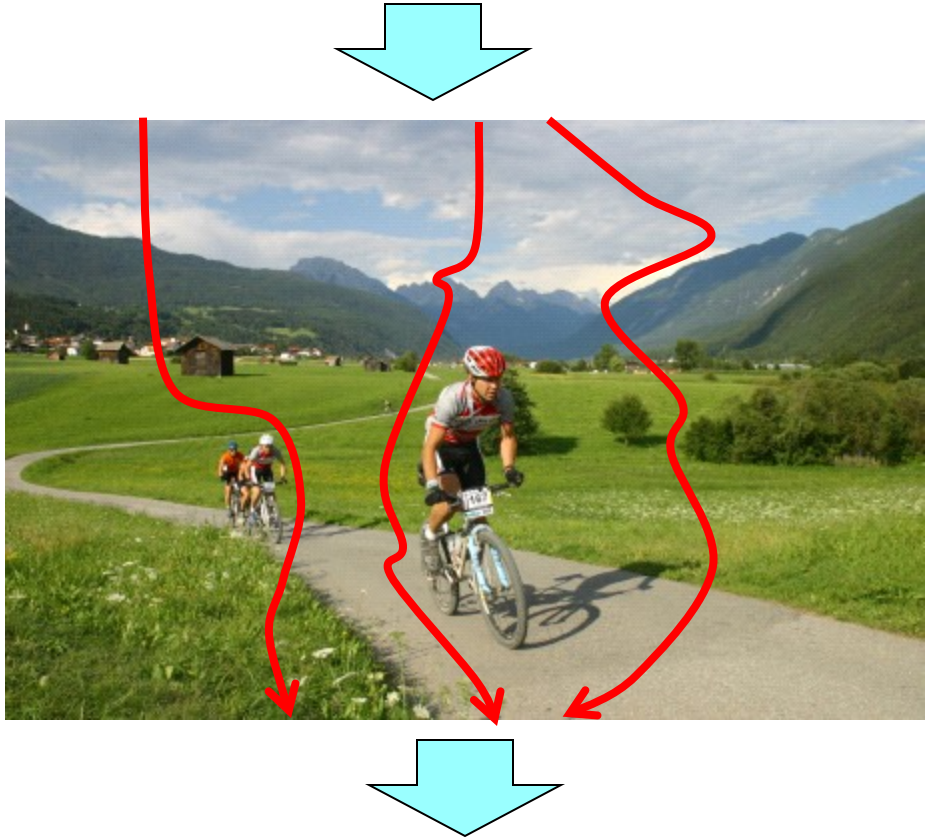
Seam Carving

- **Basic Idea: remove unimportant pixels from the image**
  - Unimportant = pixels with less “energy”

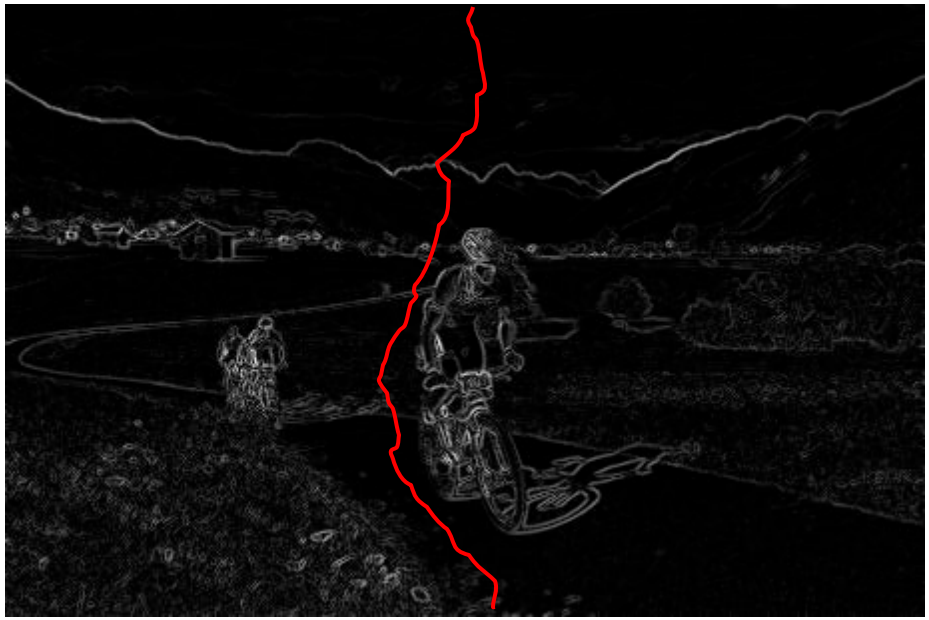
$$E_1(\mathbf{I}) = |\frac{\partial}{\partial x}\mathbf{I}| + |\frac{\partial}{\partial y}\mathbf{I}|.$$

- **Intuition for gradient-based energy:**
  - Preserve strong contours
  - Human vision more sensitive to edges – so try remove content from smoother areas
  - Simple, enough for producing some nice results
  - See their paper for more measures they have used

Finding the Seam?



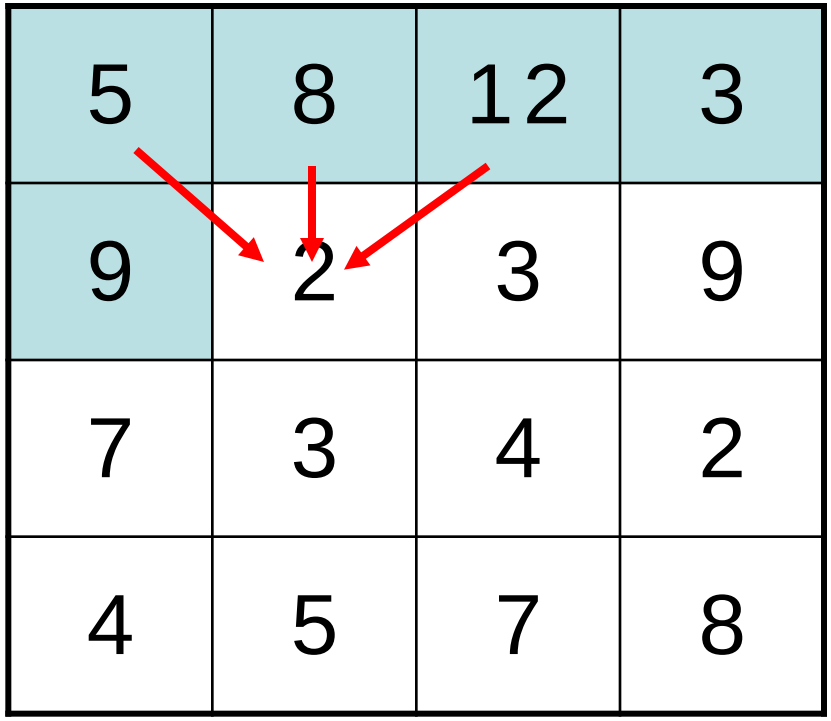
The Optimal Seam



$$E(\mathbf{I}) = \left|\frac{\partial}{\partial x}\mathbf{I}\right| + \left|\frac{\partial}{\partial y}\mathbf{I}\right| \Rightarrow s^* = \arg\min_s E(s)$$

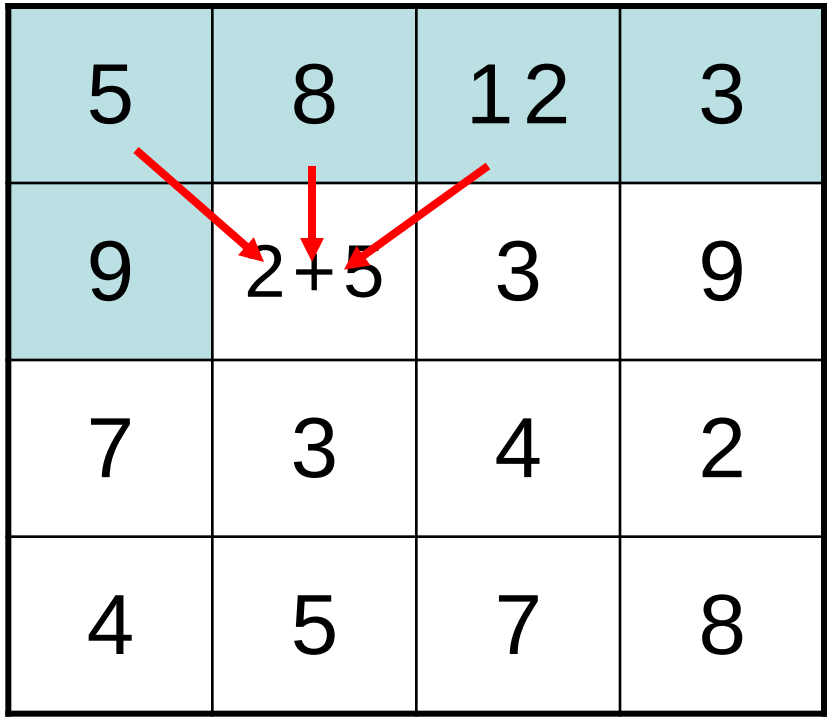
Dynamic Programming

- **Invariant property:**
  - M(i,j) = minimal cost of a seam going through (i,j) (satisfying the seam properties)



Dynamic Programming

$$\mathbf{M}(i, j) = E(i, j) + \min\left(\mathbf{M}(i-1, j-1), \mathbf{M}(i-1, j), \mathbf{M}(i-1, j+1)\right)$$



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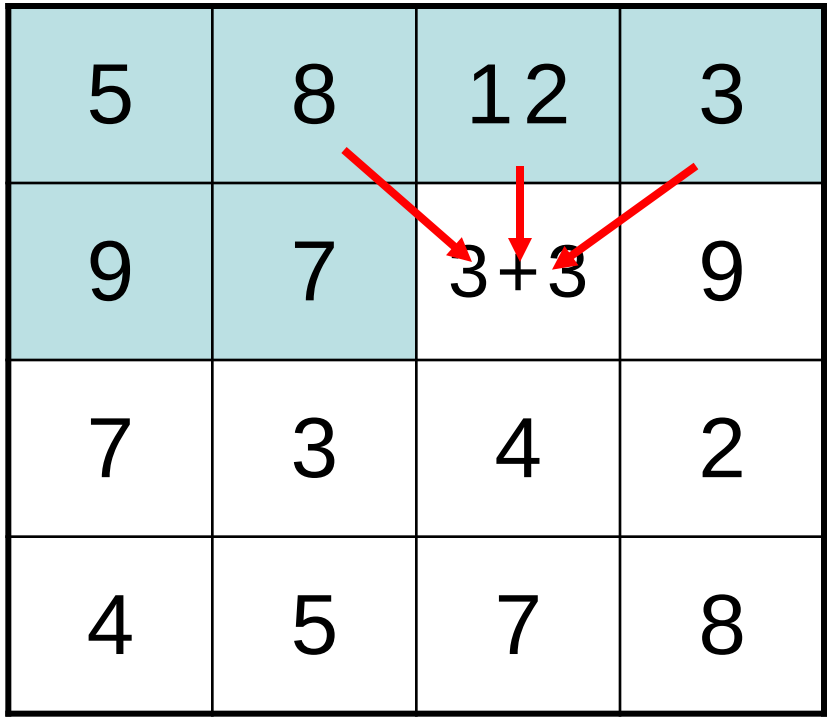

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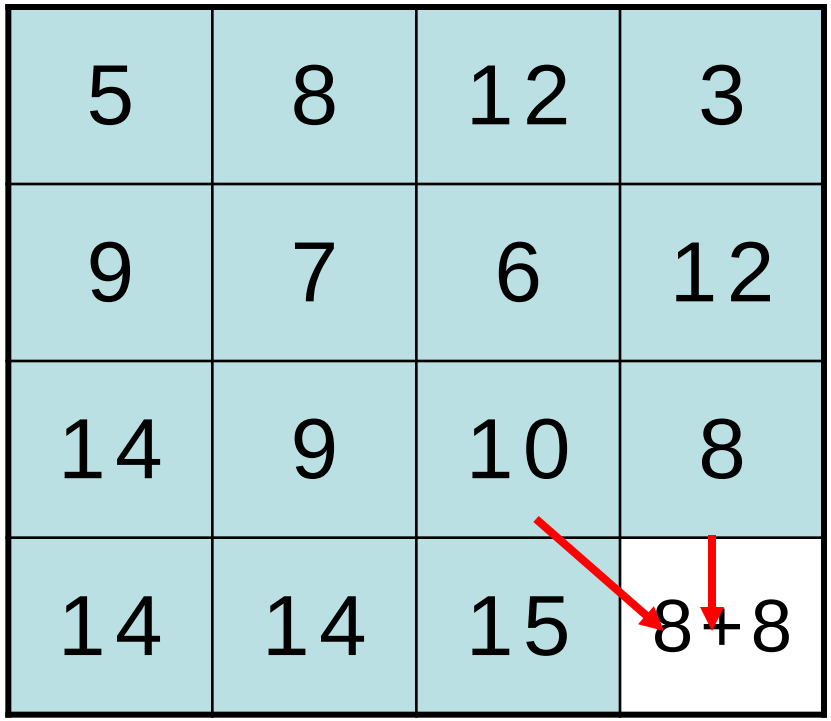
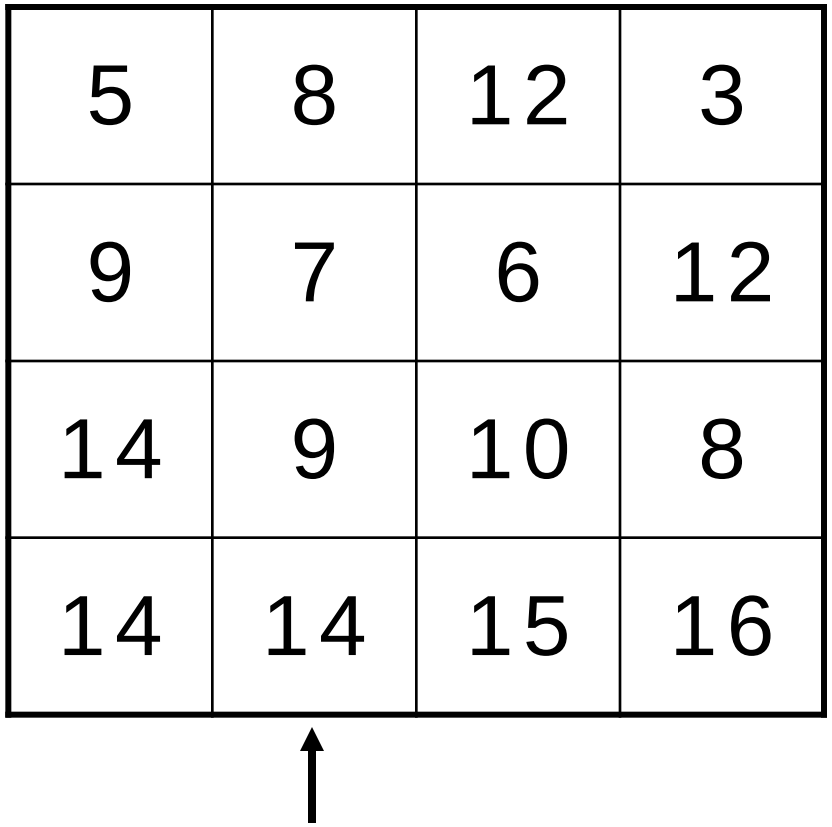
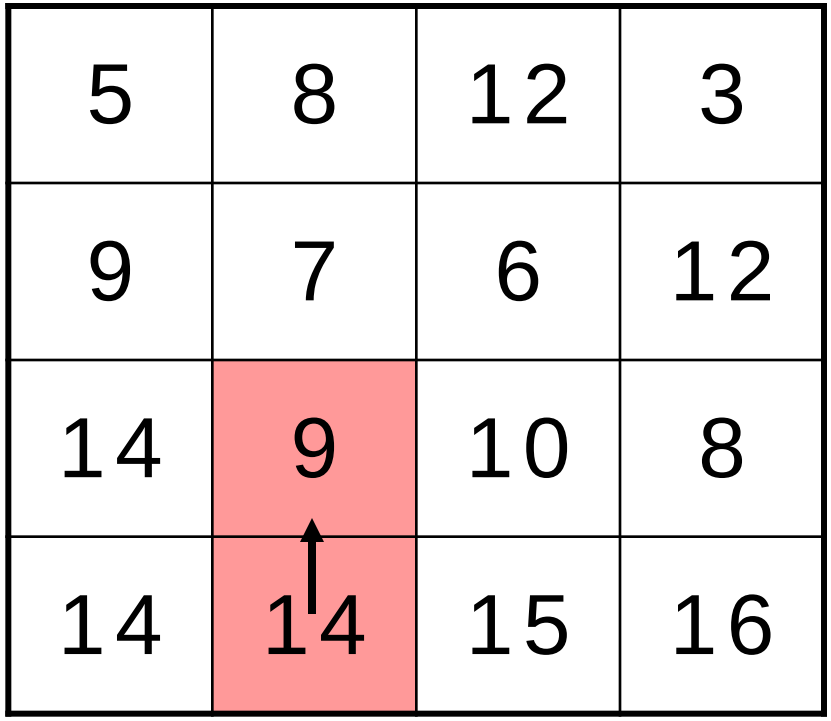


Searching for Minimum

- **Backtrack (can store choices along the path, but do not have to)**

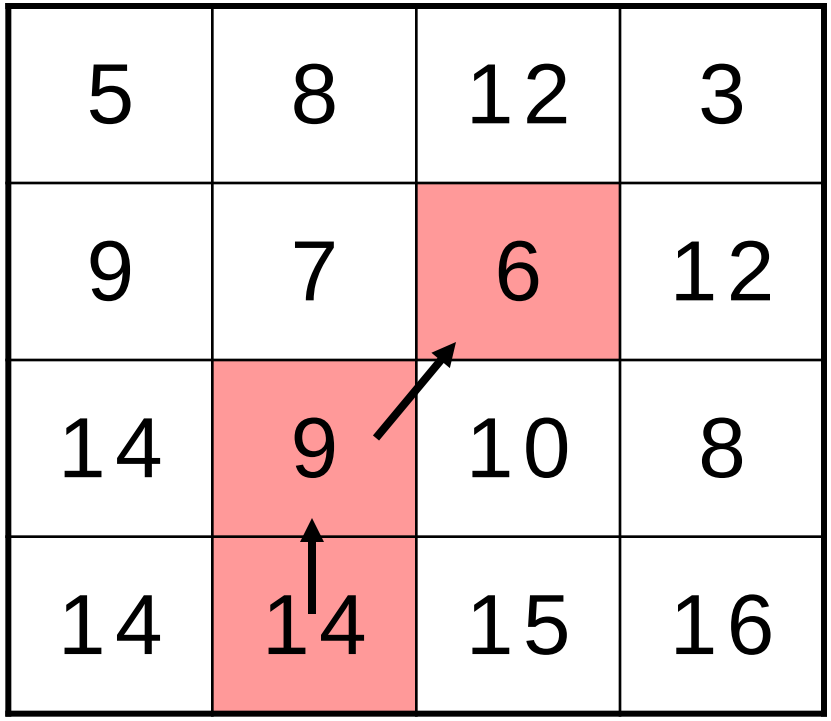


Backtracking the Seam



Michael Rubinstein — MIT CSAIL – mrub@mit.edu

Backtracking the Seam



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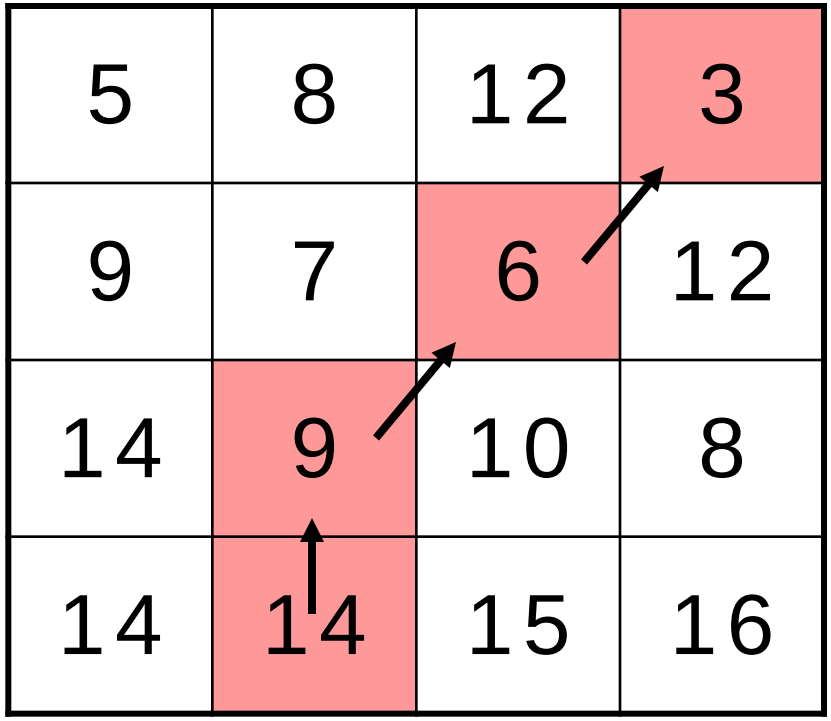
Backtracking the Seam



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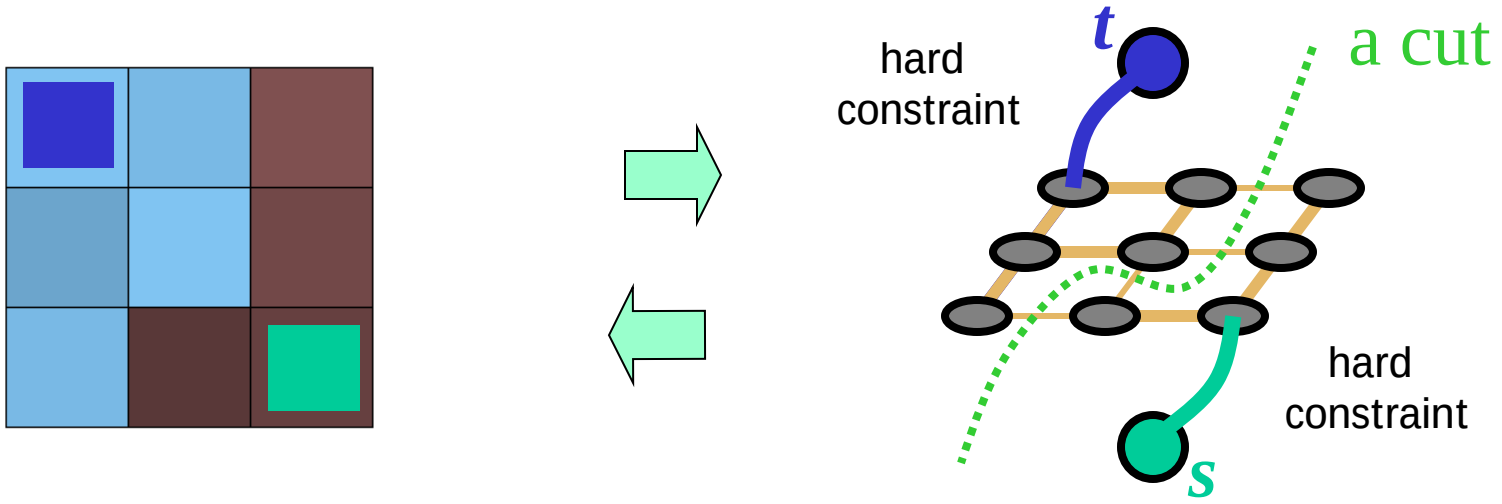
Graphcuts

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)

e.g. Lazy Snapping

Interactive segmentation using graphcuts

Also see the original Boykov&Jolly, ICCV'01,
"GrabCut", etc, etc ,etc.

Putting it all together

Compositing images

- Have a clever blending function
  - Feathering
  - blend different frequencies differently
  - Gradient based blending
- Choose the right pixels from each image
  - Dynamic programming – optimal seams
  - Graph-cuts

Now, let’s put it all together:

- Interactive Digital Photomontage, 2004 (video)

Interactive Digital Photomontage

Aseem Agarwala, Mira Dontcheva
Maneesh Agrawala, Steven Drucker, Alex Colburn
Brian Curless, David Salesin, Michael Cohen

http://www.youtube.com/watch?v=kzV-5135bGA