# Matting and Compositing





www.davehillphoto.com/adventure

Image Manipulation and Computational Photography
CS294-69 Fall 2011

Maneesh Agrawala

[Some slides from James Hays , Derek Hoiem, Alexei Efros and Fredo Durand]

## A3 Gradient/Resizing and Warping Due Mon Oct 24

Implement Gradient Domain Techniques or Resizing and Warping

#### Adequate to implement, best solutions go beyond:

Every technique has some limitations (well written papers usually describe some of them). Develop techniques to address one or more limitations?

Sometimes different papers present different techniques for addressing the same problem Implement competing techniques and compare their strengths and weaknesses.

It may be possible to combine ideas from multiple papers to produce a new hybrid technique that addresses a new problem. Develop a new way to combine the texture synthesis techniques your have read about to solve a new problem.

1 person = 1 paper,

2 people = 1 paper + issue from list above or 2 papers,

3 people = 2 papers + issue from list above

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# **Final Project**

Goal: Develop new research idea

#### Can work in groups of up to 3 people

Tell us groups by this Thursday (10/27) Will assume you are working alone unless told otherwise

Project proposals due 10/31 Proposal presentations 10/31 and 11/2 Final presentations 11/28 and 11/30 Final paper 12/7

# How Does Superman Fly?





Super-human powers?

OR

Image matting and compositing?

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http://www.petapixel.com/2011/07/21/dave-hill-photographs-deconstructed/

# Motivation: Compositing

Combining multiple images. Typically, paste a foreground object onto a new background

Movie special effect

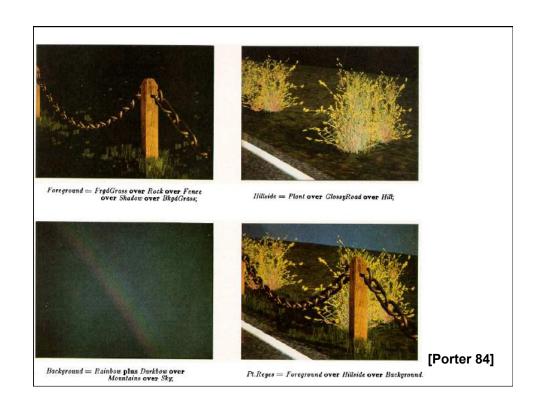
Multi-pass CG

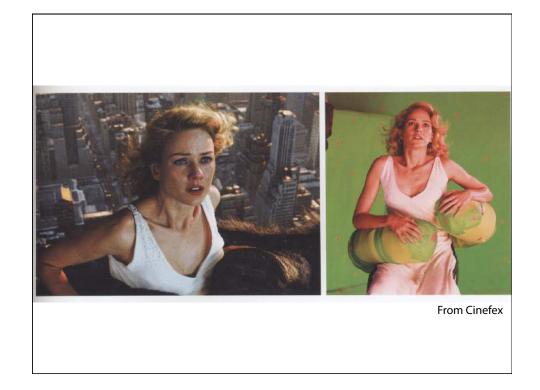
Combining CG & film

## Photo retouching

- · Change background
- · Fake depth of field
- Page layout: extract objects, magazine covers

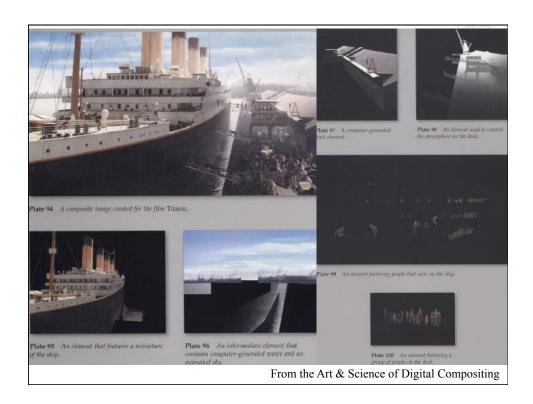
2



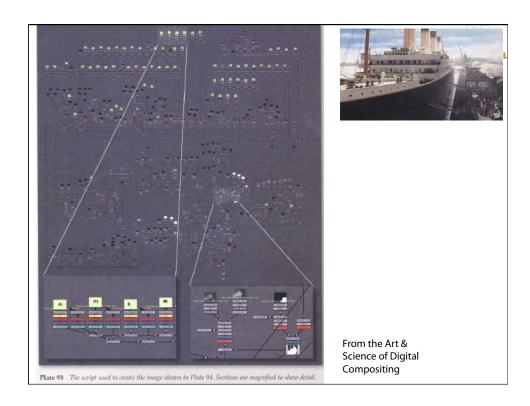


# Video

http://www.petapixel.com/2011/02/15/
amazing-effects-from-popular-tv-shows/
http://www.youtube.com/watch?v=Srt07MIrRRo

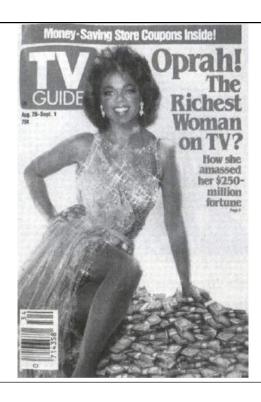


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# Forest Gump







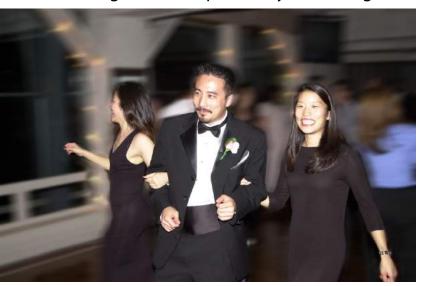
# **Photo Editing**

Edit the background independently from foreground



# **Photo Editing**

Edit the background independently from foreground



## **Technical Issues**

#### Compositing

• How exactly do we handle transparency?

#### Smart selection

• Facilitate the selection of an object

#### Matte extraction

• Resolve sub-pixel accuracy, estimate transparency

#### **Smart pasting**

- Don't be smart with copy, be smart with paste
- See gradient manipulation

#### Extension to video

• Where life is always harder

# Today

Compositing

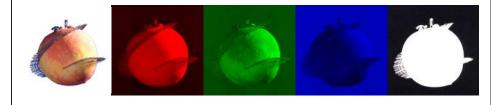
Blue screen matting

Natural image matting

# **Alpha**

 $\alpha\!\!:$  1 means opaque, 0 means transparent

32-bit images: R, G, B,  $\alpha$ 



From the Art & Science of Digital Compositing

# Why Fractional Alpha?

Motion blur, small features (hair), depth of field causes

partial occlusion







# With Binary Alpha



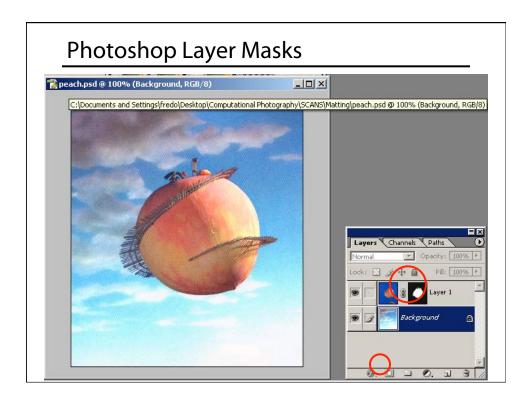
From Digital Domain

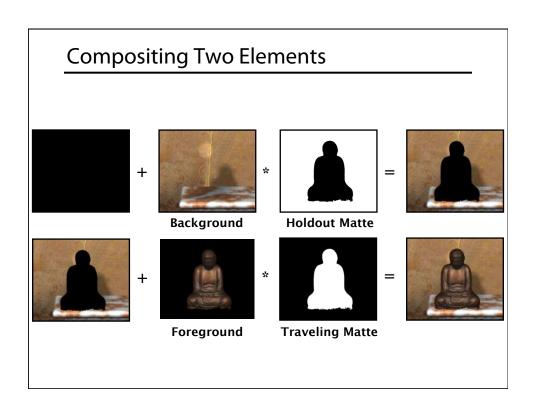
# With Fractional Alpha



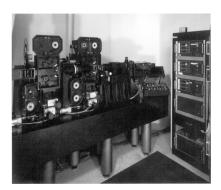
From Digital Domain

1

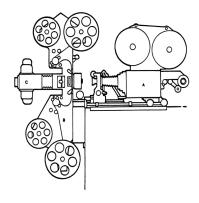




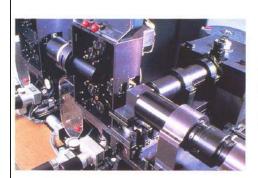
# **Optical Printing**



From: "Industrial Light and Magic," Thomas Smith (p. 181)



From: "Special Optical Effects," Zoran Perisic



Left: Close-up of the Quad printer, showing projectors (left), beam splitters (center), 4-perf camera (right), and anamorphic lens (lower right). This unit was built by ILM.

Below: ILM's original Quad printer, which was later modified and rebuilt.



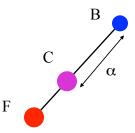
From: "Industrial Light and Magic," Thomas Smith



# Compositing

Given the foreground color F=(R<sub>F</sub>, G<sub>F</sub>, B<sub>F</sub>), the background color (R<sub>B</sub>, G<sub>B</sub>, B<sub>B</sub>) and  $\alpha$  for each pixel

The compositing (aka over) operation is:  $C=\alpha F+(1-\alpha)B$ 

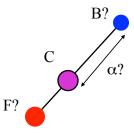


# **Matting Problem**

Inverse problem:

Assume an image is the over composite of a foreground and a background

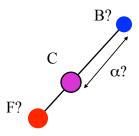
Given an image color C, find F, B and  $\alpha$  so that  $C=\alpha$  F+(1- $\alpha$ )B



# **Matting Ambiguity**

 $C=\alpha F+(1-\alpha)B$ 

How many unknowns, how many equations?

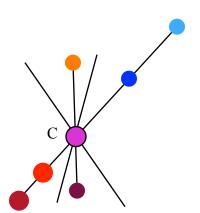


# **Matting Ambiguity**

 $C=\alpha F+(1-\alpha)B$ 

7 unknowns:  $\boldsymbol{\alpha}$  and triplets for F and B

3 equations, one per color channel



# **Matting Ambiguity**

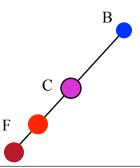
 $C=\alpha F+(1-\alpha)B$ 

7 unknowns:  $\boldsymbol{\alpha}$  and triplets for F and B

3 equations, one per color channel

With known background (e.g. blue/green screen):

4 unknowns, 3 equations



# Questions?



From Cinefex

# Traditional Blue Screen Matting

Invented by Petro Vlahos (Technical Academy Award 1995) Recently formalized by Smith & Blinn Initially for film, then video, then digital Assume that the foreground has no blue



Peter Clades

DONOR E SHITTER ADDRES

EETH REAGGEN RAMASS





From Cinefex

## Traditional Blue Screen Matting

Assume b and g channels of Fg respect  $b \le a_2 g$  for  $0.5 \le a_2 \le 1.5$ 

$$\alpha = 1 - a_1(b - a_2 g)$$

- clamped to 0 and 1
- where  $a_1$  and  $a_2$  are user parameters
- constrains Fg g to be linearly related to Fg b

Lots of refinements (see Smith & Blinn's paper)

# Blue/Green Screen Matting Issues

#### Color limitation

- Annoying for blue-eyed people
- → adapt screen color (in particular green)

#### Blue/Green spilling

- The background illuminates the foreground, blue/green at silhouettes
- Modify blue/green channel, e.g. set to min (b, a<sub>2</sub>g)

#### **Shadows**

• How to extract shadows cast on background

# Blue/Green Screen Matting Issues



From the Art & Science of Digital Compositing

# Blue Spill

http://www.digitalgreenscreen.com/figure3.html

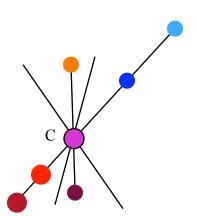


Figure 3. Firefox Blue Spill Matte Series 1, original shot. Note blue reflected on wing surfaces from bluescreen -- undesirable but unavoidable on such surfaces.

# **Recall: Matting Ambiguity**

 $C=\alpha F+(1-\alpha)B$ 

7 unknowns:  $\alpha$  and triplets for F and B 3 equations, one per color channel



# **Natural Matting**

[Ruzon & Tomasi 2000, Chuang et al. 2001] Given an input image with arbitrary background

The user specifies a coarse Trimap (specify Fg, Bg and unknown regions)

Estimate F, B, alpha in the unknown region

 We don't care about B, but it's a byproduct/unkown

Now, what tool do we know to estimate something, taking into account all sorts of known probabilities?



input (OK, could be more natural)



trimap images from Chuang et al

# Who's Afraid of Bayes?

## **Bayesian Inference**

You observe y and want to infer x that generated this y

Example: y:student wears Berkeley T-shirt

x: school the student from

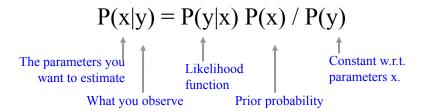
#### Bayesian approach:

define P(x|y) for each possible x to generate given observation y

Example: P(being Stanford student | given is wearing Berkeley shirt)
P(being Berkeley student | given is wearing Berkeley shirt)
P(being SF State student | given is wearing Berkeley shirt)

Usually, pick answer with highest probability

## **Bayes Theorem**



P(being Stanford student | given is wearing Berkeley shirt)

= P(wears an Berkeley shirt | given being a Stanford student)P(being a Stanford student) / P(wearing an Berkeley T shirt)

## Bayes Theorem: Semi Proof

#### Think in terms of numbers

 and count in two different ways, starting with full # of x and full # of y

#student Stanford students wearing Berkeley shirt

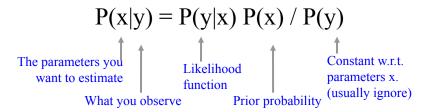
- = #Stanford student
- x Percentage(Stanford student to wear Berkeley shirt)
- = #student wearing Berkeley shirt
- x Percentage(Berkeley shirt wearers from Stanford)

#### That is

$$P(x)P(y|x)=P(y)P(x|y)$$

and thus 
$$P(x|y) = P(y|x) P(x) / P(y)$$

## Bayes theorem



 $P(Berkeley shirt | Stanford) = 1\% \qquad P(Stanford) = 20\%$   $P(Berkeley shirt | Berkeley) = 100\% \qquad P(Berkeley) = 20\%$   $P(Berkeley shirt | SF State) = 40\% \qquad P(SF State) = 60\%$ 

Therefore, if you see someone with an Berkeley shirt, a safe bet is to assume they are from which school?

Stanford "score": 0.0020

Berkeley "score": 0.2000

SF State "score": 0.2400

# **Bayes Theorem for Matting**

# Matting and Bayes

What do we observe?

#### What do we observe?

· Color C at a pixel



# Matting and Bayes

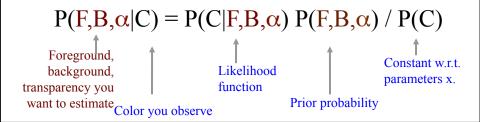
What do we observe: Color C What are we looking for?



What do we observe: Color C What are we looking for: F, B,  $\alpha$ 







# Matting and Bayes

What do we observe: Color C What are we looking for: F, B,  $\alpha$  Likelihood probability?



• Given F, B and Alpha, probability that we observe C

$$P(F,B,\alpha|C) = P(C|F,B,\alpha) \ P(F,B,\alpha) \ / \ P(C)$$
Foreground, background, transparency you transparency you want to estimate Color you observe

$$P(F,B,\alpha|C) = P(C|F,B,\alpha) \ P(F,B,\alpha) \ / \ P(C)$$
Foreground, transparency you parameters x.

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What do we observe: Color C What are we looking for: F, B,  $\alpha$  Likelihood probability?



- Given F, B and Alpha, probability that we observe C
- If measurements are perfect, probability is non-zero only if C=α F+(1-α)B
- But assume Gaussian noise with variance  $\sigma_{C}$

$$P(F,B,\alpha|C) = P(C|F,B,\alpha) \ P(F,B,\alpha) \ / \ P(C)$$
Foreground, background, transparency you want to estimate Color you observe

$$P(F,B,\alpha|C) = P(C|F,B,\alpha) \ P(F,B,\alpha) \ / \ P(C)$$

Prior probability

## Matting and Bayes

What do we observe: Color C

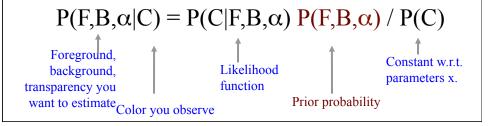
What are we looking for: F, B,  $\boldsymbol{\alpha}$ 



Likelihood probability: Compositing equation + Gaussian noise with variance  $\sigma_{\rm C}$ 

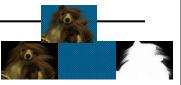
#### Prior probability:

• How likely is the foreground to have color F? the background to have color B? transparency to be  $\alpha$ ?



What do we observe: Color C

What are we looking for: F, B,  $\alpha$ 



Likelihood probability: Compositing equation + Gaussian noise with variance  $\sigma_{\rm C}$ 

Prior probability: Build a probability distribution from the known regions given by the trimap

· This is the heart of Bayesian matting

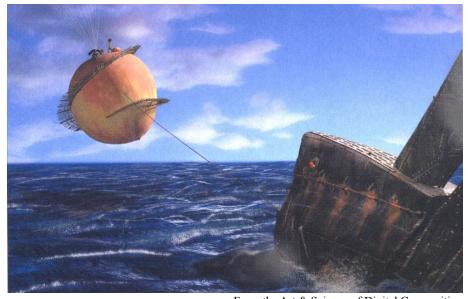
$$P(F,B,\alpha|C) = P(C|F,B,\alpha) \ P(F,B,\alpha) \ / \ P(C)$$
Foreground, background, transparency you background, function want to estimate Color you observe

$$P(F,B,\alpha|C) = P(C|F,B,\alpha) \ P(F,B,\alpha) \ / \ P(C)$$
Foreground, constant w.r.t. parameters x.

#### Note

The noise in the measurement argument is partially propaganda. A deeper reason to add a Gaussian around the measurement is to make the problem more tractable by smoothing the probability/optimization energy

## **Questions?**



From the Art & Science of Digital Compositing

## Let's Derive

Assume F, B and  $\alpha$  are independent

$$P(F,B,\alpha|C) = P(C|F,B,\alpha) P(F,B,\alpha) / P(C)$$
$$= P(C|F,B,\alpha) P(F) P(B) P(\alpha) / P(C)$$

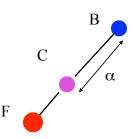
But multiplications are hard!

Make life easy, work with log probabilities L means log P here:

$$L(F,B,\alpha|C) = L(C|F,B,\alpha) +$$
  
 
$$L(F) + L(B) + L(\alpha) - L(C)$$

And ignore L(C) because it is constant

# Log Likelihood: $L(C|F,B,\alpha)$



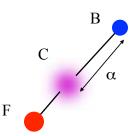
# Log Likelihood: $L(C|F,B,\alpha)$



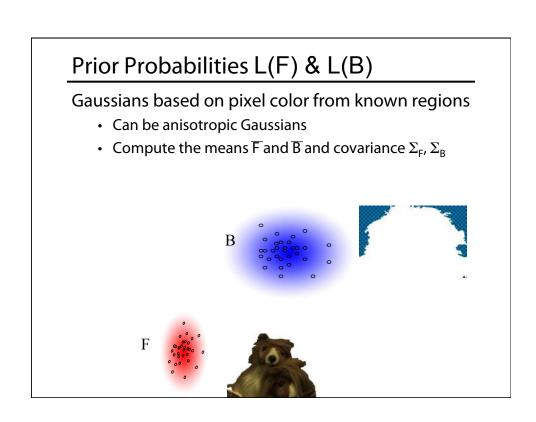
Gaussian noise model:

 $\frac{-\text{color difference}^2}{\sigma_C^2}$ 

Take the log: L(C|F,B,
$$\alpha$$
)= -  $||C - \alpha F - (1-\alpha) B||^2 / \sigma^2_C$ 



# 



# Prior Probabilities L(F) & L(B)

Gaussians based on pixel color from known regions

$$ar{F} = rac{1}{N_F} \sum F_i$$
  $\Sigma_F = rac{1}{N_F} \sum (F_i - ar{F})(F_i - ar{F})^T$ 

$$L(F) = -(F - \bar{F})^T \Sigma_F^{-1} (F - \bar{F})/2$$

Same for B





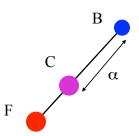
# Prior Probabilities $L(\alpha)$

What about alpha?

Well, we don't really know anything

Keep  $L(\alpha)$  constant; essentially ignore it

- But see coherence matting for a prior on  $\boldsymbol{\alpha}$ 



## **Bayesian Matting Equation**

Maximize  $L(C|F,B,\alpha) + L(F) + L(B) + L(\alpha)$ 

$$L(C|F,B,\alpha) = -\|C - \alpha F - (1-\alpha) B\|2 / \sigma^{2}_{C}$$

$$L(F) = -(F - \bar{F})^{T} \Sigma_{F}^{-1} (F - \bar{F}) / 2$$

$$L(B) = -(B - \bar{B})^{T} \Sigma_{B}^{-1} (B - \bar{B}) / 2$$

Unfortunately, not a quadratic equation because of the product  $(1-\alpha)$  B

 $\rightarrow$  iteratively solve for F,B and for  $\alpha$ 

#### For α Constant

Derive  $L(C|F,B,\alpha) + L(F) + L(B) + L(\alpha)$  wrt F & B, and set to zero gives

$$\begin{bmatrix} \Sigma_F^{-1} + I\alpha^2/\sigma_C^2 & I\alpha(1-\alpha)/\sigma_C^2 \\ I\alpha(1-\alpha)/\sigma_C^2 & \Sigma_B^{-1} + I(1-\alpha)^2/\sigma_C^2 \end{bmatrix} \begin{bmatrix} F \\ B \end{bmatrix}$$
$$= \begin{bmatrix} \Sigma_F^{-1}\overline{F} + C\alpha/\sigma_C^2 \\ \Sigma_B^{-1}\overline{B} + C(1-\alpha)/\sigma_C^2 \end{bmatrix},$$

#### For F & B constant

Derive L(C|F,B, $\alpha$ ) + L(F) +L(B)+L( $\alpha$ ) wrt  $\alpha$ , and set to zero gives

$$\alpha = \frac{(C-B) \cdot (F-B)}{\|F-B\|^2}$$

# Recap: Bayesian Matting

The user specifies a trimap Compute Gaussian distributions F,  $\Sigma_{\rm F}$  and B,  $\Sigma_{\rm B}$  for foreground and background regions



#### **Iterate**

- Keep  $\alpha$  constant, solve for F & B (for each pixel)
- Keep F & B constant, solve for  $\alpha$ ((for each pixel)

Note that pixels are treated independently

## **Additional Gimmicks**

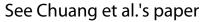
#### Use multiple Gaussians

- Cluster the pixels into multiple groups
- Fit a Gaussian to each cluster
- Solve for all the pairs of F & B Gaussians
- · Keep the highest likelihood

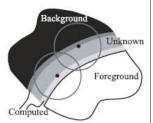
#### Use local Gaussians

• Not on the full image

#### Solve from outside-in

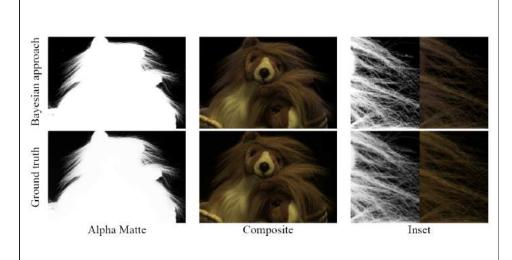


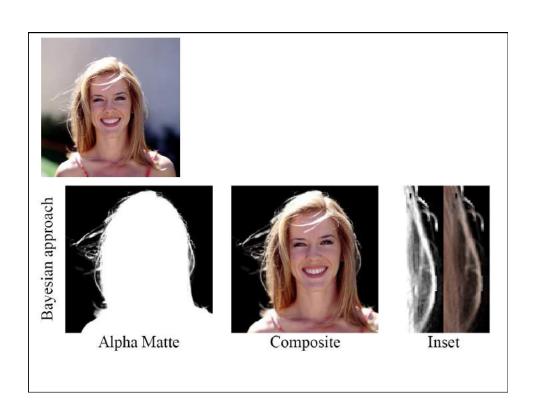
http://grail.cs.washington.edu/projects/digital Computer matting/

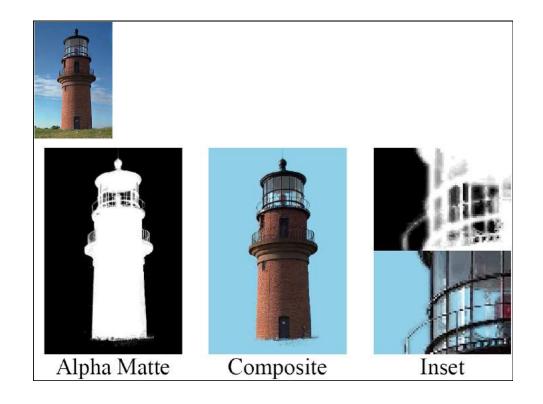


## Results

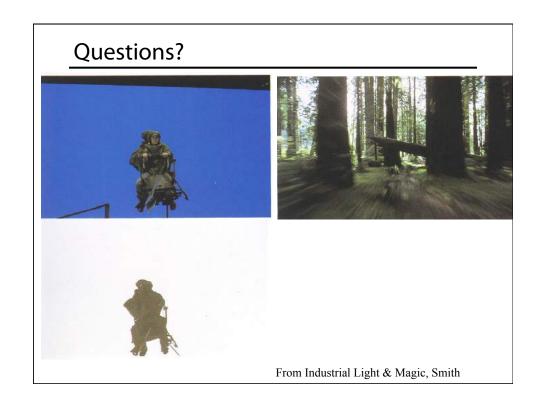
From Chuang et al. 2001











## **Extensions: Video**

Interpolate trimap between frames
Exploit the fact that background might become visible
http://grail.cs.washington.edu/projects/digital-matting/
video-matting/

