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 you 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
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?
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
Foreground = Foliage over Rock over Fence over Shadow over Highland.

Hillsides = Plastic over GlossyRoad over Hill.

Background = Rainshadow plus Farshadow over Mountains over Sky.

Pt. Reyes = Foreground over Hillsides over Background.

[Porter 84]

From Cinefex
Video

http://www.petapixel.com/2011/02/15/amazing-effects-from-popular-tv-shows/
http://www.youtube.com/watch?v=Srt07MlRRo

From the Art & Science of Digital Compositing
From the Art & Science of Digital Compositing

Forest Gump
Page Layout, Magazine Covers
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**

α: 1 means opaque, 0 means transparent

32-bit images: R, G, B, α

From the Art & Science of Digital Compositing

**Why Fractional Alpha?**

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

From the Art & Science of Digital Compositing
With Binary Alpha

From Digital Domain

With Fractional Alpha

From Digital Domain
Photoshop Layer Masks

Compositing Two Elements

\[
\text{Background} + \text{Foreground} \times \text{Holdout Matte} = \text{Foreground} + \text{Foreground} \times \text{Traveling Matte} = \text{Foreground}
\]
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 \( F = (R_F, G_F, B_F) \), the background color \( (R_B, G_B, B_B) \) 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?

7 unknowns: \( \alpha \) and triplets for \( F \) and \( B \)
3 equations, one per color channel
Matting Ambiguity

\[ C = \alpha F + (1 - \alpha)B \]

7 unknowns: \( \alpha \) 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

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

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

- 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, g)

Shadows
- How to extract shadows cast on background

Plate 52  (b) The element placed into the scene without spill suppression. Note the blue fringes on the subject, particularly in the hair.

From the Art & Science of Digital Compositing
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/unknown

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

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: \( P(\text{being Stanford student} | \text{given is wearing Berkeley shirt}) \)
\( P(\text{being Berkeley student} | \text{given is wearing Berkeley shirt}) \)
\( P(\text{being SF State student} | \text{given is wearing Berkeley shirt}) \)

Usually, pick answer with highest probability

Bayes Theorem

\[
P(x|y) = \frac{P(y|x) \ P(x)}{P(y)}
\]

The parameters you want to estimate
What you observe
Likelihood function
Prior probability
Constant w.r.t. parameters \( x \).

\( P(\text{being Stanford student} | \text{given is wearing Berkeley shirt}) \)
= \( P(\text{wears an Berkeley shirt} | \text{given being a Stanford student}) \)
\( P(\text{being a Stanford student}) / P(\text{wearing an Berkeley T shirt}) \)
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
\[ P(x|y) = \frac{P(y|x)P(x)}{P(y)} \]

Bayes theorem

\[ P(x|y) = P(y|x)P(x)/P(y) \]

The parameters you want to estimate
What you observe
Prior probability
Likelihood function
Constant w.r.t. parameters x.
(usually ignore)

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

Therefore, if you see someone with a 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

\[ P(x|y) = \frac{P(y|x) \ P(x)}{P(y)} \]

The parameters you want to estimate
What you observe
Likelihood function
Prior probability
Constant w.r.t. parameters \( x \).

Matting and Bayes

What do we observe?

\[ P(x|y) = \frac{P(y|x) \ P(x)}{P(y)} \]

The parameters you want to estimate
What you observe
Likelihood function
Prior probability
Constant w.r.t. parameters \( x \).
Matting and Bayes

What do we observe?
- Color C at a pixel

\[ P(x|C) = \frac{P(C|x) P(x)}{P(C)} \]

The parameters you want to estimate
Color you observe
Likelihood function
Prior probability
Constant w.r.t. parameters x.

Matting and Bayes

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

\[ P(x|C) = \frac{P(C|x) P(x)}{P(C)} \]

The parameters you want to estimate
Color you observe
Likelihood function
Prior probability
Constant w.r.t. parameters x.
Matting and Bayes

What do we observe: Color C
What are we looking for: F, B, α

\[ P(F,B,α|C) = \frac{P(C|F,B,α) P(F,B,α)}{P(C)} \]

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

\[ P(F,B,α|C) = \frac{P(C|F,B,α) P(F,B,α)}{P(C)} \]

Constant w.r.t. parameters x.
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 \( C \)
- If measurements are perfect, probability is non-zero only if \( C = \alpha F + (1-\alpha)B \)
- But assume Gaussian noise with variance \( \sigma_C \)

\[
P(F,B,\alpha|C) = \frac{P(C|F,B,\alpha) P(F,B,\alpha)}{P(C)}
\]

Foreground, background, transparency you want to estimate

Color you observe

Likelihood function

Prior probability

Constant w.r.t. parameters \( x \).

Matting and Bayes

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

Likelihood probability: Compositing equation + Gaussian noise with variance \( \sigma_C \)

Prior probability:
- How likely is the foreground to have color \( F \)? the background to have color \( B \)? transparency to be \( \alpha \)?

\[
P(F,B,\alpha|C) = \frac{P(C|F,B,\alpha) P(F,B,\alpha)}{P(C)}
\]

Foreground, background, transparency you want to estimate

Color you observe

Likelihood function

Prior probability

Constant w.r.t. parameters \( x \).
Matting and Bayes

What do we observe: Color C
What are we looking for: F, B, α

Likelihood probability: Compositing equation + Gaussian noise with variance $\sigma_C$

Prior probability: Build a probability distribution from the known regions given by the trimap
- This is the heart of Bayesian matting

$$P(F,B,\alpha|C) = \frac{P(C|F,B,\alpha) \cdot P(F,B,\alpha)}{P(C)}$$

- Foreground, background, transparency you want to estimate
- Color you observe
- Likelihood function
- Prior probability
- 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?

Let's Derive

Assume F, B and \( \alpha \) are independent

\[
P(F,B,\alpha|C) = \frac{P(C|F,B,\alpha) \ P(F,B,\alpha)}{P(C)}
\]

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

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

Gaussian noise model:

$$e^{-\frac{||C - \alpha F - (1-\alpha) B||^2}{\sigma_C^2}}$$

Take the log:

$$L(C|F,B,\alpha) = - \frac{||C - \alpha F - (1-\alpha) B||^2}{\sigma_C^2}$$
Prior Probabilities $L(F) \& L(B)$

Gaussians based on pixel color from known regions

- Can be anisotropic Gaussians
- Compute the means $F$ and $B$ and covariance $\Sigma_F, \Sigma_B$
Prior Probabilities $L(F)$ & $L(B)$

Gaussians based on pixel color from known regions

$$\bar{F} = \frac{1}{N_F} \sum F_i \quad \Sigma_F = \frac{1}{N_F} \sum (F_i - \bar{F})(F_i - \bar{F})^T$$

$$L(F') = -(F' - \bar{F})^T \Sigma_F^{-1} (F' - \bar{F})/2$$

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 $\alpha$
Bayesian Matting Equation

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

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

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

$$L(B) = -\frac{(B - \bar{B})^T \Sigma_B^{-1} (B - \bar{B})}{2}$$

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

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

For $\alpha$ Constant

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

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

See Chuang et al.'s paper [here](http://grail.cs.washington.edu/projects/digital/matting/)

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Results

From Chuang et al. 2001
Questions?

From Industrial Light & Magic, Smith
Extensions: Video

Interpolate trimap between frames
Exploit the fact that background might become visible

Video Matting of Complex Scenes

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