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
Page layout, magazine covers

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 homework (pyramid splining)
  - See also in a couple weeks (gradient manipulation)
- **Extension to video**
  - Where life is always harder

**Alpha**
- $\alpha$: 1 means opaque, 0 means transparent
- 32-bit images: R, G, B, $\alpha$

**Why fractional alpha?**
- Motion blur, small features (hair) cause partial occlusion

**With binary alpha**

**With fractional alpha**

From the Art & Science of Digital Compositing

From Digital Domain

From Digital Domain
Photoshop layer masks

What does \( R, G, B, \alpha \) represent?

- \( \alpha \): 1 means opaque, 0 means transparent
- But what about \( R, G, \) and \( B? \)

Two possible answers:
- Premultiplied: the color of the object is \( R/\alpha, G/\alpha, B/\alpha \)
- or not: the color of the object is \( R, G, B \), and these values need to be multiplied by \( \alpha \) for compositing

Pre-multiplied alpha

- \((R, G, B, \alpha)\) means that the real object color is \((R/\alpha, G/\alpha, B/\alpha)\) and transparency is \( \alpha \).
- Motivated by supersampling for antialiasing in CG

\[ \{R, G, B, \alpha_i\} \]

 supersampled pixel

\[ \frac{1}{n} \sum R_i, \frac{1}{n} \sum G_i, \frac{1}{n} \sum B_i, \frac{1}{n} \sum \alpha_i \]

 resampled (averaged value)

- If I combine multiple subpixels, the same operations apply to the four channels
  - In particular if I transform the image for scale/rotate

The compositing equation

Porter & Duff Siggraph 1984

- Given Foreground \( F_A \) and Background \( F_B \) images
- For premultiplied alpha:
  \[ \text{Output} = F_A + (1-\alpha_A) F_B \]
- For non-premultiplied:
  \[ \text{Output} = \alpha F_A + (1-\alpha) F_B \]

Composing Two Elements

Optical Printing

From: “Industrial Light and Magic,” Thomas Smith (p. 181)
From: “Special Optical Effects,” Zoran Perisic

Slide from Pat Hanrahan

Slide from Pat Hanrahan
Limitations of alpha

- Hard to represent stainglasses
  - It focuses on subpixel occlusion (0 or 1)
- Does not model more complex optical effects
  - e.g. magnifying glass

Questions?

Compositing

- Non premultiplied version:
  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 over operation is: $C=\alpha F + (1-\alpha)B$
  - (in the premultiplied case, omit the first $\alpha$)

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: \( \alpha \) and triplets for F and B
- 3 equations, one per color channel

Questions?

Traditional blue screen matting

- Assume that blue \( b \) and green \( g \) channels of the foreground respect \( b \leq a_2 g \)
  for \( a_2 \) typically between 0.5 and 1.5
- \( \alpha = 1 - a_1 (b - a_2 g) \)
  - clamped to 0 and 1
  - \( a_1 \) and \( a_2 \) are user parameters
  - Note that \( \alpha = 1 \) where assumption holds

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
- Note that computation of \( \alpha \) has to be analog, needs to be simple enough

With known background (e.g. blue/green screen):
- 4 unknowns, 3 equations

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

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Extension: Chroma key

- Blue/Green screen matting exploits color channels
- Chroma key can use an arbitrary background color
- See e.g.
  - Keith Jack, "Video Demystified", Independent Pub Group (Computer), 1996

Questions?

- **Hint:** PSet 2 solution is in next slides

  - **Hint 2:** start problem set 2 early!
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 (known Foreground, known background and unknown region)
- Goal: 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?

Bayes theorem

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

Matting and Bayes

- What do we observe?
  - Color \( C \) at a pixel

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

Matting and Bayes

- What do we observe?
  - Color \( C \) at a pixel

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

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

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

Foreground, background, transparency you want to estimate: Color you observe, Prior probability

Matting and Bayes

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

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 \( \sigma_C \)

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

Foreground, background, transparency you want to estimate: Color you observe, Prior probability

Matting and Bayes

- What do we observe: Color C
- What are we looking for: F, B, \( \alpha \)
- Prior probability: Build a probability distribution from the known regions
  - This is the heart of Bayesian matting

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

Foreground, background, transparency you want to estimate: Color you observe, Prior probability
Questions?

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

- Gaussian noise model: \( \frac{-\text{color difference}^2}{\sigma_C^2} \)
- Take the log: \( L(C|F,B,\alpha) = - \frac{||C - \alpha F - (1-\alpha) B||^2}{\sigma_C^2} \)
- Unfortunately not quadratic in all coefficients (product \( \alpha B \))

Prior probabilities \( L(F) \) & \( L(B) \)

- Gaussians based on pixel color from known regions
  - Can be anisotropic Gaussians
  - Compute the means \( \overline{F} \) and \( \overline{B} \) and covariance \( \Sigma_F, \Sigma_B \)

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

Prior probabilities \( L(F) \) & \( L(B) \)

- Gaussians based on pixel color from known regions

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 and ignore it
  - But see coherence matting for a prior on $\alpha$

**Recap: Bayesian matting equation**

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

\[
L(C|F,B,\alpha) = - ||C - \alpha F - (1-\alpha) B||^2 / \sigma^2_C
\]

\[
L(F) = -(F - \bar{F})^T \Sigma^{-1}_F (F - \bar{F}) / 2
\]

\[
L(B) = -(B - \bar{B})^T \Sigma^{-1}_B (B - \bar{B}) / 2
\]

- 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

\[
\begin{bmatrix}
\Sigma^{-1}_F + I\alpha^2/\sigma^2_C & I\alpha(1-\alpha)/\sigma^2_C \\
I\alpha(1-\alpha)/\sigma^2_C & \Sigma^{-1}_B + I(1-\alpha)^2/\sigma^2_C
\end{bmatrix}
\begin{bmatrix}
F \\
B
\end{bmatrix}
=
\begin{bmatrix}
\Sigma^{-1}_F + C\alpha/\sigma^2_C \\
\Sigma^{-1}_B + C(1-\alpha)/\sigma^2_C
\end{bmatrix}
\]

**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 $F$ & $B$
  - Keep $F$ & $B$ constant, solve for $\alpha$
  - for each pixel
- Note that pixels are treated independently
Questions?

Additional gimmicks (not on p-set!)

- 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

Results

- From Chuang et al. 2001

See Chuang et al. 2001
Questions?

Extensions: Video

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

Environment matting

Model complex optical effects
Each pixel can depend on many background pixels

References

- Smith & Blinn 1996 http://portal.acm.org/citation.cfm?id=537263
  Formal treatment of Blue screen
- Ruzon & Tomasi 2000 http://ai.stanford.edu/~ruzon/alpha/
The breakthrough that renewed the issue (but not crystal clear)
- Brinkman’s Art & Science of Digital Compositing
  – Not so technical, more for practitioners
MoreRefs

Matting:
- http://www.csl.isy.liu.se/~ces/publications/ChunmingChuang03.pdf

Chroma Key:
- http://www.vce.com/bluescreen.html
- http://www.pixelpainter.com/NAB/Blue_vs_Green_Screen_for_DV.pdf

Petro Vlahos (inventor of blue screen matting):

To buy a screen:

Superman & blue screen:

Recap: Bayes cookbook

- Express everything you know as probabilities
  - Use Gaussians everywhere. Maybe multiple of them.
  - Learn from examples when you have them
  - Hack a noise model when you don't
  - Leave constant when desperate
  - More precisely, use a Gaussian noise to express the likelihood to observe the input given any parameter in the solution space
    - Soft consistency constraint
- Work in the log domain where everything is additive
- Find the maximum