Photographic compositions

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Use of mattes for compositing

The Great Train Robbery (1903) matte shot

Use of mattes for compositing

The Great Train Robbery (1903) matte shot

Optical compositing

King Kong (1933) Stop-motion + optical compositing
Digital matting and composting

The lost world (1925)  The lost world (1997)
Miniature, stop-motion  Computer-generated images

Optical compositing  Blue-screen matting, digital composition, digital matte painting

Titanic  background replacement
Matting and Compositing  background editing
Matting and Compositing

King Kong (1933)  Jurassic Park III (2001)
**Digital matting: bluescreen matting**

*Forrest Gump (1994)*

- The most common approach for films.
- Expensive, studio setup.
- Not a simple one-step process.

**Color difference method (Ultimatte)**

\[ C = F + \alpha B \]

- Blue-screen photograph
- Spill suppression: \( \text{if } B > G \text{ then } B = G \)
- Matte creation: \( \alpha = B - \max(G, R) \)
  - demo with Paint Shop Pro (\( B = \min(B, G) \))

**Problems with color difference**

Background color is usually not perfect! (lighting, shadowing...)

**Chroma-keying (Primatte)**
Chroma-keying (Primatte)

demo

Outline

• Traditional matting and compositing
• The matting problem
• Bayesian matting and extensions
• Matting with less user inputs
• Matting with multiple observations
• Beyond the compositing equation*
• Conclusions

Compositing

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

foreground color alpha matte background plate

\[ F \]
\[ \alpha \]
\[ B \]

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

compositing equation

\[ \alpha = 0 \]

\[ \alpha = 1 \]

Compositing
Compositing

Matting

Three approaches:
1. Reduce number of unknowns
2. Add observations
3. Add priors

Matting (reduce number of unknowns)
Matting (reduce #unknowns)

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

Matting (add observations)

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

Matting (add priors)

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

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Bayesian framework

Parameters $z \rightarrow f(z) + \varepsilon \rightarrow y$ observed signal

$z^* = \max_z P(z \mid y)$
$= \max_z \frac{P(y \mid z) P(z)}{P(y)}$
$= \max_z L(y \mid z) + L(z)$

Bayesian framework

Example:
- super-resolution
- de-blurring
- de-blocking

$\arg \max_{F, B, \alpha} P(F, B, \alpha \mid C)$
$= \arg \max_{F, B, \alpha} \frac{P(C \mid F, B, \alpha) P(F) P(B) P(\alpha)}{P(C)}$

$L(C \mid F, B, \alpha) = -\|C - \alpha F - (1 - \alpha) B\|^2 / 2 \sigma_C^2$

Bayesian framework

Priors

$F = \frac{1}{W} \sum_{i \in I} w_i F_i$
$\Sigma_F = \frac{1}{W} \sum_{i \in I} w_i (F_i - \overline{F})(F_i - \overline{F})^T$

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

\begin{align*}
&\arg \max_{F,B,\alpha} L(C \mid F, B, \alpha) + L(F) + L(B) \\
&\arg \max_{F,B,\alpha} -\|C - \alpha F - (1 - \alpha) B\|^2 / \sigma_C^2 \\
&\quad - (F - \overline{F})^T \Sigma_F^{-1} (F - \overline{F}) / 2 \\
&\quad - (B - \overline{B})^T \Sigma_B^{-1} (B - \overline{B}) / 2
\end{align*}

Bayesian image matting

Optimization

repeat

1. fix \( \alpha \)

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

2. fix \( F \) and \( B \)

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

until converge

Bayesian image matting
Comparisons

Video matting

Video matting
Video matting
optical flow
Comparison without background with background
Problems with Bayesian matting

- It requires fine trimaps for good results
- It is tedious to generate fine trimaps
- Its performance rapidly degrades when foreground and background patterns become complex
- There is no direct and local control to the resulted mattes
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**Motivation**

\[
E(X) = \sum_{i \in \mathcal{V}} E_1(x_i) + \lambda \sum_{(i,j) \in \mathcal{E}} E_2(x_i, x_j)
\]

\[
E_1(x_i = 1) = 0 \quad E_1(x_i = 0) = \infty \quad \forall i \in \mathcal{F}
\]

\[
E_1(x_i = 1) = \infty \quad E_1(x_i = 0) = 0 \quad \forall i \in \mathcal{B}
\]

\[
E_1(x_i = 1) = \frac{d^T}{d_x + d_y} \quad E_1(x_i = 0) = \frac{d^B}{d_x + d_y} \quad \forall i \in \mathcal{U}
\]
Matting approaches

- Sampling approaches: solve for each alpha separately by utilizing local fg/bg samples, e.g. Ruzon/Tomasi, Knockout and Bayesian matting.
- Propagation approaches: solve the whole matte together by optimizing, e.g. Poisson, BP, random walker, closed-form and robust matting.

Poisson matting

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

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

\[ \nabla \alpha \approx \frac{1}{F - B} \nabla I \]

\[ \alpha^* = \arg \min_{\alpha} \int \int_{p \in \Omega} \left\| \nabla \alpha_p - \frac{1}{F_p - B_p} \nabla I_p \right\|^2 dp \]
**Poisson matting**

**Robust matting**

- Jue Wang and Michael Cohen, CVPR 2007

**Robust matting**

- Instead of fitting models, a non-parametric approach is used

Bayesian

Robust

**Robust matting**

- We must evaluate hypothesized foreground/background pairs

\[
\hat{\alpha} = \frac{(C - B^j)(F^i - B^j)}{\|F^i - B^j\|^2}
\]

distance ratio

\[
R_d(F^i, B^j) = \frac{\| C - (\hat{\alpha}F^i + (1 - \hat{\alpha})B^j) \|}{\| F^i - B^j \|}
\]
Robust matting

- To encourage pure fg/bg pixels, add weights

\[ w(F^i) = \exp\left\{ - \frac{\| F^i - C \|^2}{D_F} \right\}, \quad \min_i(\| F^i - C \|) \]

\[ w(B^j) = \exp\left\{ - \frac{\| B^j - C \|^2}{D_B} \right\}, \quad \min_j(\| B^j - C \|) \]

- Combine them together. Pick up the best 3 pairs and average them

\[ f(F^i, B^j) = \exp\left\{ - \frac{R_d(F^i, B^j)^2 \cdot w(F^i) \cdot w(B^j)}{\sigma^2} \right\} \]
Matte optimization

Solved by Random Walk Algorithm

Matte optimization

data constraints

\[
W(i, F) = \gamma \cdot \left[ \hat{f}_i \hat{\alpha}_i + (1 - \hat{f}_i)\delta(\hat{\alpha}_i > 0.5) \right]
\]

\[
W(i, B) = \gamma \cdot \left[ \hat{f}_i (1 - \hat{\alpha}_i) + (1 - \hat{f}_i)\delta(\hat{\alpha}_i < 0.5) \right]
\]

neighborhood constraints

\[
W_{ij} = \sum_{k}^{(i,j) \in W_k} \frac{1}{9} (1 + (C_i - \mu_k)(\Sigma_k + \frac{\epsilon}{9f})^{-1}(C_j - \mu_k))
\]

Demo (EZ Mask)

Evaluation

- 8 images collected in 3 different ways
- Each has a “ground truth” matte
**Evaluation**

- Mean square error is used as the accuracy metric
- Try 8 trimaps with different accuracy for testing robustness
- 7 methods are tested: Bayesian, Belief propagation, Poisson, Random Walk, KnockOut2, Closed-Form and Robust matting

**Quantitative evaluation**

**Subjective evaluation**
Subjective evaluation

Ranks of these algorithms

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Accuracy</th>
<th>Robustness</th>
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<tbody>
<tr>
<td>Poisson</td>
<td>6.9</td>
<td>6.8</td>
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<tr>
<td>Random walk</td>
<td>6.0</td>
<td>4.4</td>
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<tr>
<td>Knockout2</td>
<td>4.5</td>
<td>4.5</td>
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<tr>
<td>Bayesian</td>
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<td>6.0</td>
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<tr>
<td>Belief Propagation</td>
<td>3.3</td>
<td>3.1</td>
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<td>Close-form</td>
<td>2.6</td>
<td>2.0</td>
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<tr>
<td>Robust matting</td>
<td>1.0</td>
<td>1.3</td>
</tr>
</tbody>
</table>

Summary

- Propagation-based methods are more robust
- Sampling-based methods often generate more accurate mattes than propagation-based ones with fine trimaps
- Robust matting combines strengths of both

Soft scissor

- Jue Wang et. al., SIGGRAPH 2007
- Users interact in a similar way to intelligent scissors
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Matting with multiple observations
• Invisible lights
  - Polarized lights
  - Infrared
• Thermo-key
• Depth Keying (ZCam)
• Flash matting

Invisible lights (Infrared)
Invisible lights (Infared)
Invisible lights (Polarized)

Thermo-Key
ZCam

Defocus matting

Matting with camera arrays
Flash matting

Foreground flash matting equation

\[ I' = I^f - I = \alpha(F^f - F) = \alpha F' \]

Generate a trimap and directly apply Bayesian matting.

\[
\begin{align*}
    L(I' | \alpha, F') &= -||I' - \alpha F'||^2 / \sigma^2_{I'} \\
    L(F') &= -(F' - \overline{F'})^T \Sigma_{F'}^{-1}(F' - \overline{F'})
\end{align*}
\]
\[ I = \alpha F + (1 - \alpha)B \]
\[ I' = \alpha F' \]

arg \( \max_{\alpha, F, B, F'} \) \( L(\alpha, F, B, F' | I, I') \)

\[ = \arg \max_{\alpha, F, B, F'} \{ L(I | \alpha, F, B) + L(I' | \alpha, F') + \]
\[ L(F) + L(B) + L(F') + L(\alpha) \} \]

**Joint Bayesian flash matting**

\[ \alpha = \frac{\sigma_{F'}^2 (F - B)^T (I - B) + \sigma_{F'}^2 F' F'}{\sigma_{F'}^2 (F - B)^T (F - B) + \sigma_{F'}^2 F' F'} \]

\[ = \begin{bmatrix}
\Sigma_{F}^{-1} + I\alpha^2 / \sigma_I^2 & I\alpha(1 - \alpha)\sigma_I^2 & 0 \\
I\alpha(1 - \alpha)\sigma_I^2 & \Sigma_B^{-1} + I\alpha^2 / \sigma_I^2 & 0 \\
0 & 0 & \Sigma_{F'}^{-1} + I\alpha^2 / \sigma_{F'}^2
\end{bmatrix}
\begin{bmatrix}
F \\
B \\
F'
\end{bmatrix} \]

**Comparison**

**Joint Bayesian flash matting**

**Comparison**

**Joint Bayesian flash matting**
Flash matting

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Conclusions
- Matting algorithms improve a lot in these 10 years
- In production, it is still always preferable to shoot against uniform backgrounds
- Algorithms for more complex backgrounds
- Devices or algorithms for automatic matting