

# Possion Matting

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Presented by Robert Jacques on 9/24/2007

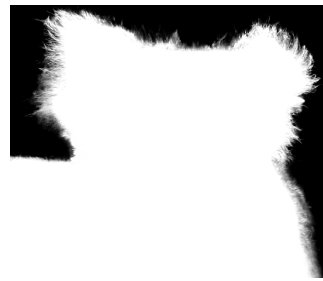
## Outline

- What is Image Matting?
- Related Work
- Poisson Matting
  - Global Matting
  - Local Matting
- Results

## Original Koala



## High Quality Poisson Matte



## Extracted Koala with blue background



## Composite Koala



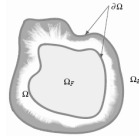
## What is Image Matting?

- Model an image as a blend of foreground and background

$$I_{x,y} = \alpha_{x,y} F_{x,y} + (1 - \alpha_{x,y}) B_{x,y}$$

- Finding  $\alpha$ ,  $F$  and  $B$  from  $I$  is the pulling of the matte problem

- Under constrained
- Trimap
  - Definite foreground
  - Definite background
  - Unknown



## Related Work

- Color statistics

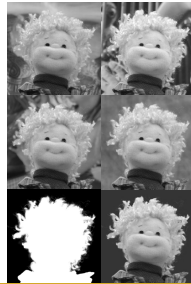
- Ruzon and Tomasi 2000
  - Un-oriented Gaussians
- Berman et al. 2000, Knockout
  - Weighted average of perimeter pixels.
- Hillman et al. 2001
  - PCA
- Chuang et al. 2001, Bayesian Matting
  - Maximum a posterior on oriented Gaussian clusters
  - Previous best



## Related Work

- Other Techniques

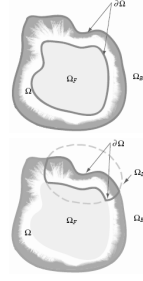
- Smith and Blinn 1996
  - Triangulation using 2 images with different known backgrounds
- Qian and Sezan 1999, Difference Matting
  - 2 images, one with and one without the background
- Chuang et al. 2002, Video matting
  - Bayesian matting using optical flow to propagate the trimap between frames



## Related Work

- Lessons learned

- A human needs to be in the loop
  - Manual tweaking key to matting performance
  - Rich set of controls required
- Color Statistics
  - Error-prone in complex scenes
  - No local/manual refinement



## Poisson Matting

1. Estimate the gradient of the matte [Mitsunaga et al. 1995]

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

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

If  $F$  and  $B$  are smooth, i.e.  $\nabla F$  &  $\nabla B$  are small, then

$$(F - B) \nabla \alpha \gg \alpha \nabla F + (1 - \alpha) \nabla B$$

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

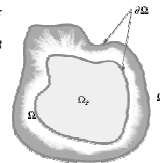
$$\alpha^* = \arg \min_{\alpha} \iint_{\Omega_U} \left\| \nabla \alpha_p - \frac{1}{F_p - B_p} \nabla I_p \right\|^2 dp \quad \alpha_p|_{\Omega_U} = \begin{cases} 1 & p \in \Omega_F \\ 0 & p \in \Omega_B \end{cases}$$

2. Solve the associated Poisson equation.

$$\Delta \alpha = \operatorname{div} \left( \frac{\nabla I}{F - B} \right)$$

## Global Poisson Matching

1. Approximate  $(F - B)$  using nearest  $\Omega_F$  and  $\Omega_B$
2. Gaussian smooth the  $(F - B)$  image
3. Reconstruct  $\alpha$  using the Poisson equation
4. Add all pixels with  $\alpha > 0.95$  to  $\Omega_F$
5. Add all pixels with  $\alpha < 0.05$  to  $\Omega_B$
6. Repeat until
  1. Convergence of  $\alpha$
  2. No pixels added to  $\Omega_F$  or  $\Omega_B$



## Local Poisson Matting



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

$$A = \frac{1}{F - B}$$

$$D = \alpha \nabla F + (1 - \alpha)\nabla B$$

$$\nabla \alpha = A(\nabla I - D)$$



$$\alpha^* = \arg \min_{\alpha} \iint_{p \in \Omega_f \cap \Omega} \left\| \nabla \alpha_p - \frac{1}{F_p - B_p} (\nabla I_p - D_p) \right\|^2 dp \quad \alpha_p|_{\partial \Omega} = \begin{cases} 1 & p \in \Omega_f \\ 0 & p \in \Omega_b \\ \alpha_{global} & p \in \Omega \end{cases}$$

## Local Operators

1. Channel Selection
  - Optional: Diffusion filtering
2. High-pass filtering
3. Boosting Brush
4. Clone Brush
- Optional
  - Erase Brush
    - Remove unwanted alpha matt directly
  - Inverse Brush
    - Inverse the sign of the matt gradient

### 1: Channel selection

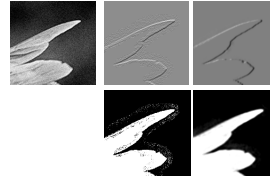
- Goal is to create a new channel  $I^* = \mathbf{w} \cdot \mathbf{I}^T$  that minimizes background or foreground variation
- 1. User selects color samples, local operator region
- 2. Minimize sample variation

$$\min_{a,b,c} \sum_i (\mathbf{w} \cdot \mathbf{I}^T - \mathbf{w} \cdot \bar{\mathbf{I}}^T)^2 \text{ s.t. } w_R + w_G + w_B = 1$$



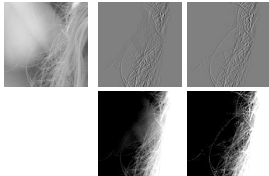
### 1-1: Diffusion Filtering

- $\nabla I$  is sensitive to JPEG blocking and noise
- Filter  $I$  with anisotropic diffusion then recompute  $\nabla I$
- Useful for hard edges



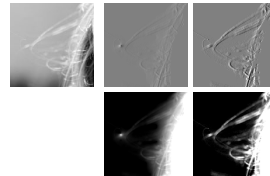
### 2: High-pass Filter

- Estimates  $D$  with a lowpass filter  $D = K * \nabla I$
- Synergistic with channel selection  $K = N(p; p_0, \sigma^2)$



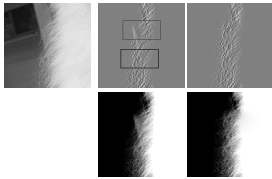
### 3: Boosting brush

- Directly increase or decrease  $A$



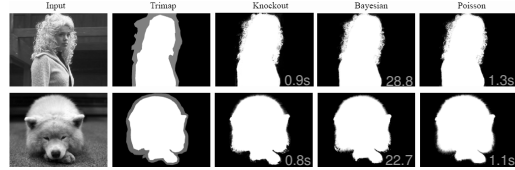
#### 4: Clone Brush

- Directly copy the matt gradient  $A(\nabla I - \mathbf{D})$
- For when the gradients are indistinguishable

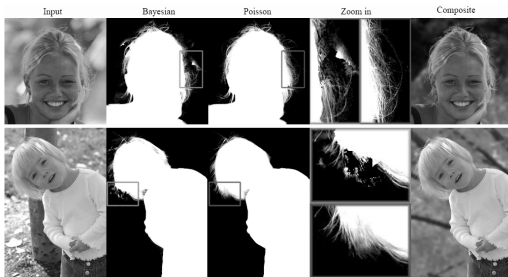


#### Results

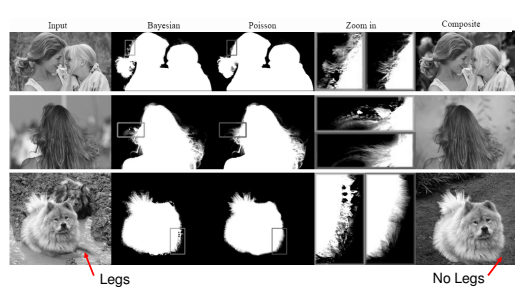
- ~7-20 local refinements per image
- <10 minutes total processing time



#### Results

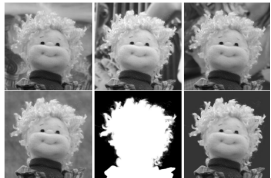


#### Results



#### Applications

- Multi-background
  - Mean image improves results by smoothing  $B$
  - Backgrounds don't have to be known



#### Applications

- Defogging
  - $$I = I_{Clear}e^{-\beta d} + Fog(1 - e^{-\beta d})$$
  - $$\nabla I_{Clear} = \nabla Ie^{-\beta d}$$
  - $\beta$  is the scatter coefficient
  - $d$  is the depth value
  - Local refinement of  $e^{-\beta d}$  using the boosting brush
  - Model from Narasimhan and Nayar 2003

## Defogging



## Defogging



## Video



## Questions?

