

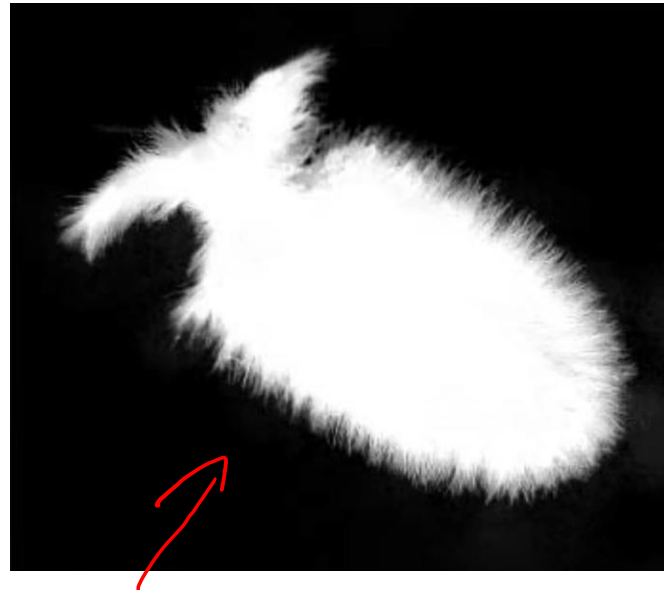
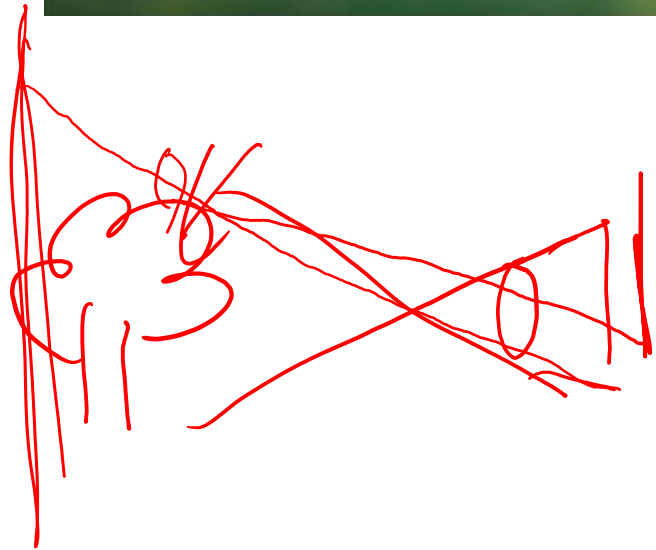
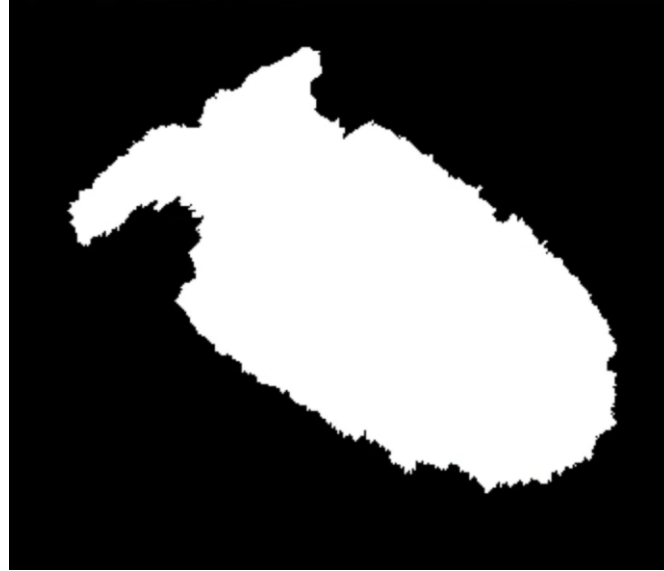
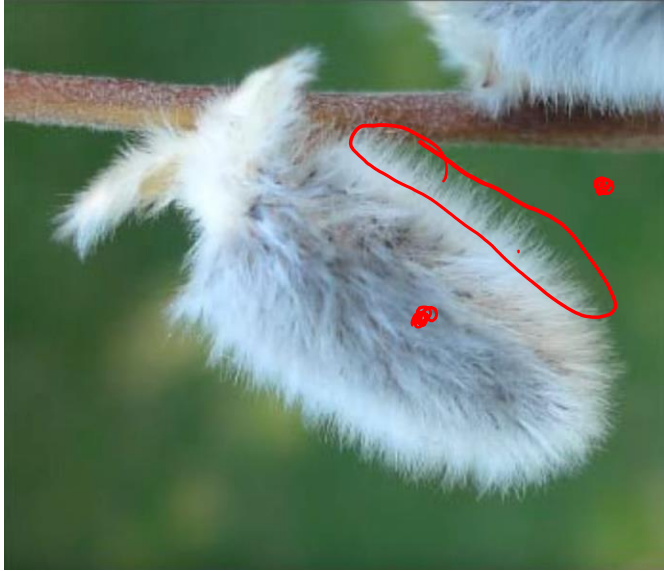
Lecture 23 Bayesian Matting

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SIST Building 2 302-F

Motivation

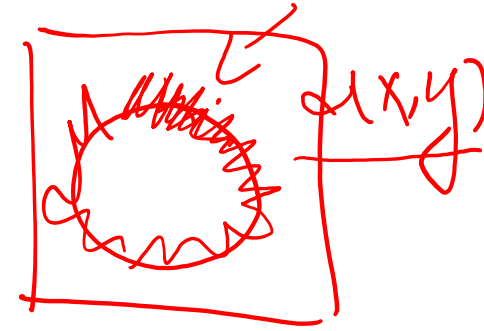
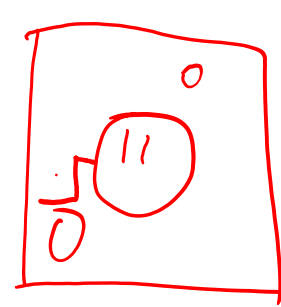


Motivation



Introduction

Foreground



- Basic function of image matting

$$I(x, y) = \alpha(x, y)F(x, y) + [1 - \alpha(x, y)]B(x, y)$$

$I(x, y), F(x, y), B(x, y)$: Full RGB image;

$\alpha(x, y)$: gray level image

$[0, 1]$

$[0, 1]$
0.6, 0.8

Background

- What is the function of α 's?

Finite pixel size

Finite shutter spread

Motion blur

Wispieness/ fuzziness/ Translucency

Why is matting hard?

$$I(x, y) = \alpha(x, y)F(x, y) + [1 - \alpha(x, y)]B(x, y)$$

known: $I(x, y) = \begin{bmatrix} R \\ G \\ B \end{bmatrix} \leftarrow \text{gray level image}$

unknown: $\alpha(x, y)$, $F(x, y) = \begin{bmatrix} R \\ G \\ B \end{bmatrix}$, $B(x, y) = \begin{bmatrix} R \\ G \\ B \end{bmatrix}$

- 3 equations in 7 unknowns



Vlahos blue-screen matting

$$\alpha = 1 - \underbrace{a_1}_{\approx} (I_b - \underbrace{a_2}_{\times} I_g)$$



a1=2,a2=1



a1=1,a2=1



a1=2,a2=2

Vlahos blue-screen matting



$a_1=1, a_2=1$



$a_1=2, a_2=1$



$a_1=2, a_2=2$

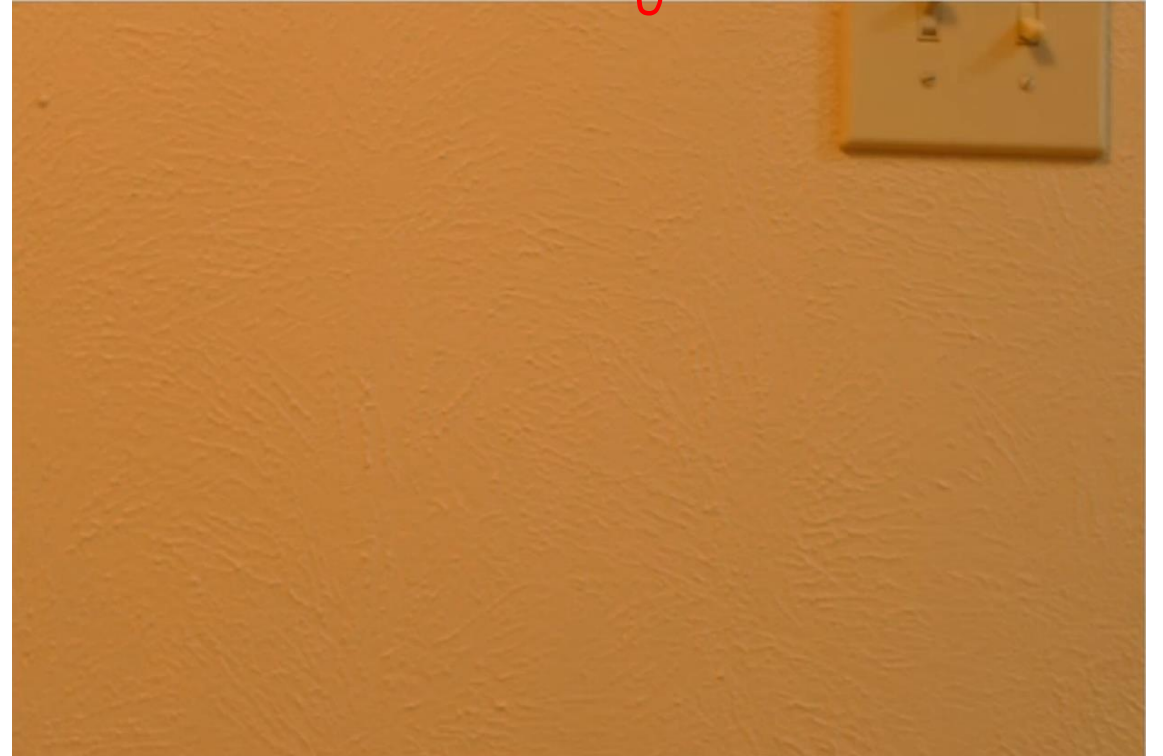


Getting ground-truth matting

$I(x, y)$



$B(x, y)$



Getting ground-truth matting

$$I = \underbrace{\alpha}_1 \cdot \underbrace{F}_3 + [1 - \alpha] \cdot B$$

When B is known, 3 equations in 4 unknowns.

Take 2 images with different known background.

$$\left\{ \begin{array}{l} I_1 = \alpha \cdot F + [1 - \alpha] \cdot B_1 \\ I_2 = \alpha \cdot F + [1 - \alpha] \cdot B_2 \end{array} \right.$$

Then 6 equations in 4 unknowns.

F α

Bayesian image matting

- Known: $I(x,y)$, full RGB
- Unknown: $\alpha(x,y)$ gray level image; $F(x,y), B(x,y)$: full RGB
- Optimization target:

$$\arg \max P(F, B, \alpha | I) = \max \frac{P(I | F, B, \alpha) P(F, B, \alpha)}{P(I)}$$

$$\text{Bayesian rule: } P(B|A) = \frac{P(A|B)P(B)}{P(A)}$$

Bayesian image matting

- Take logs:

$$\arg \max \log P(F, B, \alpha | I) \approx \log(P(I | F, B, \alpha)) + \log(P(F, B, \alpha))$$

Handwritten notes: $\log P(I) = 1 = 0$ and $-\log I$

- Then we assume $P(F, B, \alpha) = P(F) P(B) P(\alpha)$, and get:

$$\arg \max \log P(F, B, \alpha | I) \approx \log(P(I | F, B, \alpha)) + \log(P(F)) + \log(P(B)) + \log(P(\alpha))$$

Data term

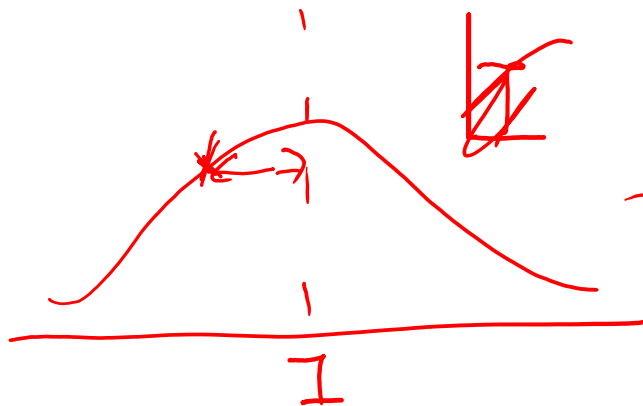
Prior term

Bayesian image matting

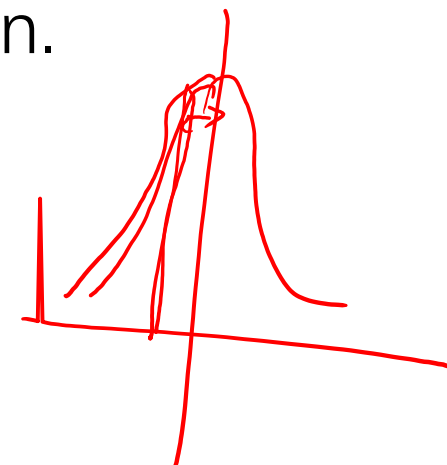
- Data term:

$$\arg \max \log P(F, B, \alpha | I) = \log \left[e^{-\frac{1}{2\sigma^2} \|I - (\alpha \cdot F + [1-\alpha] \cdot B)\|^2} \right]$$

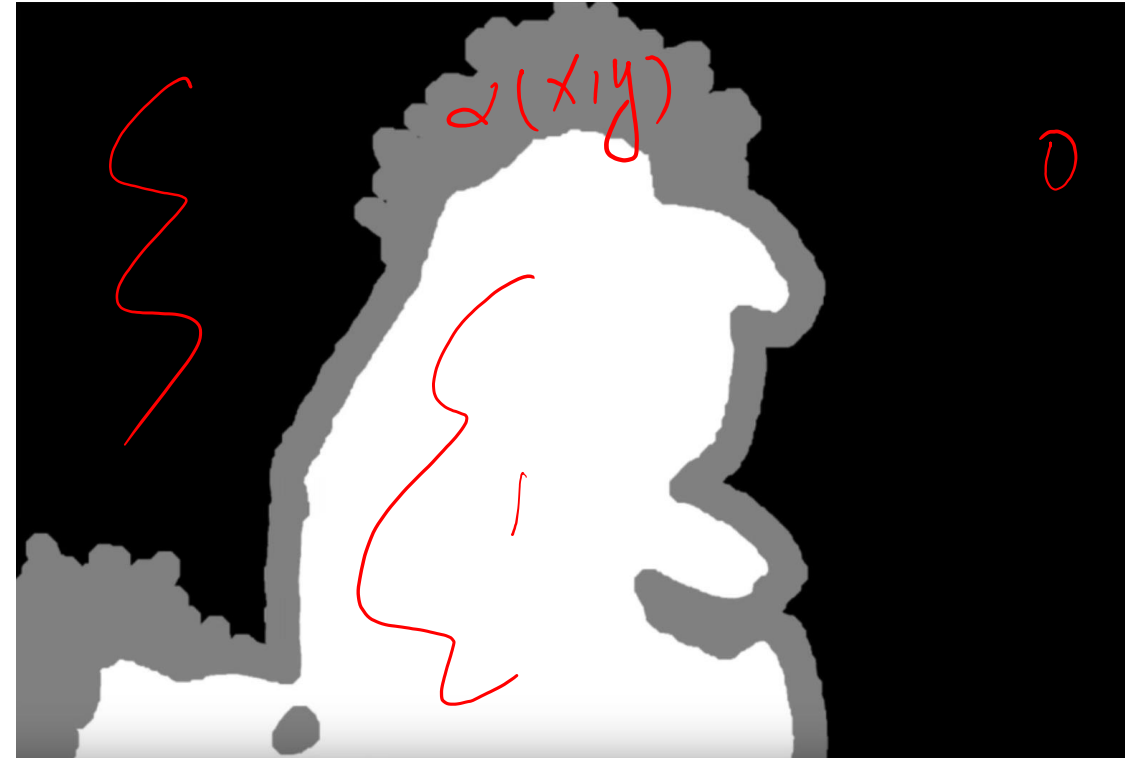
- I, F, B, α should be consistent with the matting equation.
- σ is tunable equation.



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



Trimap



$$\alpha \in (0, 1)$$

Bayesian image matting

- Prior term:

$P(F)$, $P(B)$, $P(\alpha)$ comes from trimap/ scribbles.

- Gaussian assumption for $P(F)$ and $P(B)$.
- Constant assumption for $P(\alpha)$.
- Fit Gaussian PDFs to color labeled in the trimap:

$$P(B) = \frac{1}{2\pi\sigma} e^{-\frac{1}{2\sigma^2}(B-\mu_B)^2 \Sigma_B^{-1}(B-\mu_B)}$$

$$\begin{bmatrix} 6 \times 6 \end{bmatrix} \begin{bmatrix} I \\ B \end{bmatrix} = \begin{bmatrix} 6 \times 1 \end{bmatrix} \leftarrow \text{Bayesian image matting}$$

- Taking partial derivatives for F and B then equals to 0 and we get estimation of F and B .

$$\arg \max \log P(F, B, \alpha | I) \approx \log(P(I | F, B, \alpha)) + \log(P(F)) + \log(P(B)) + \log(P(\alpha))$$

Data term

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

$$\alpha = \frac{(I - B)(F - B)}{(F - B)(F - B)}$$

Handwritten notes and terms:

- $-\frac{1}{2\sigma^2} \|I - (\alpha F + (1 - \alpha) B)\|^2$
- $-\frac{1}{2\sqrt{2\pi}\sigma^2} (B - Y_B)^T \Sigma_B^{-1} (B - Y_B)$
- $-\frac{1}{2\sqrt{2\pi}\sigma^2} (F - Y_F)^T \Sigma_F^{-1} (F - Y_F)$

- Then α can be calculated with:

<https://grail.cs.washington.edu/projects/digital-matting/papers/cvpr2001.pdf>

Results of Bayesian image matting



Take home message

- Blue screen matting
- Ground-truth matting
- Bayesian image matting
- Closed form matting