Matting and Compositing

Digital Visual Effects, Spring 2008
Yung-Yu Chuang
2008/4/29

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

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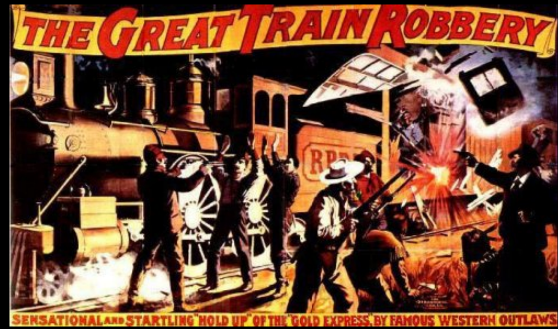
Photomontage

The Two Ways of Life, 1857, Oscar Gustav Rejlander
Printed from the original 32 wet collodion negatives.

Photographic compositions

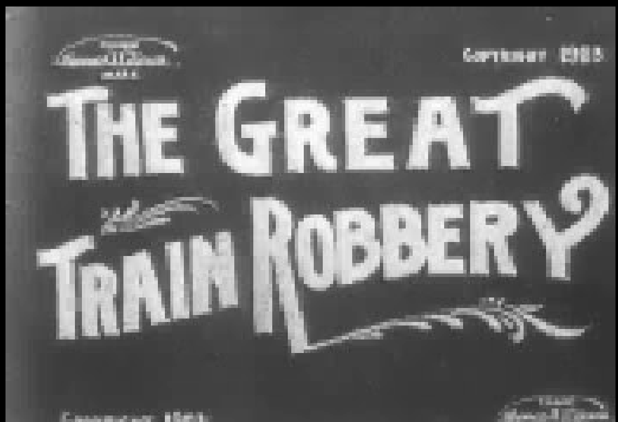
Lang Ching-shan

Use of mattes for compositing



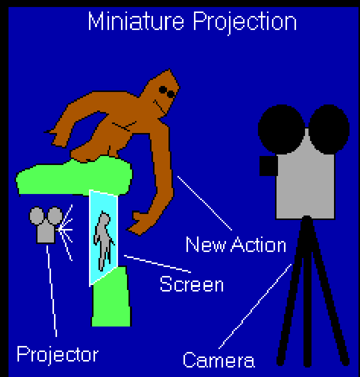
The Great Train Robbery (1903) matte shot

Use of mattes for compositing



The Great Train Robbery (1903) matte shot

Optical compositing



King Kong (1933) Stop-motion + optical compositing

Digital matting and compositing

The lost world (1925)

Miniature, stop-motion

The lost world (1997)

Computer-generated images

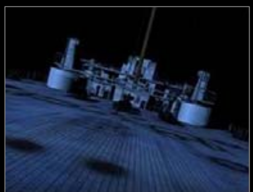
Digital matting and compositing

King Kong (1933)

Optical compositing

Jurassic Park III (2001)

Blue-screen matting,
digital composition,
digital matte painting



Titanic

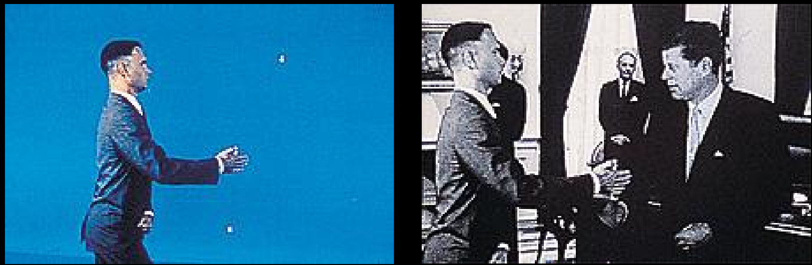
Matting and Compositing

background
replacement

background
editing

Matting and Compositing

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)

$C=F+\bar{\alpha}B$	F	$\bar{\alpha}$

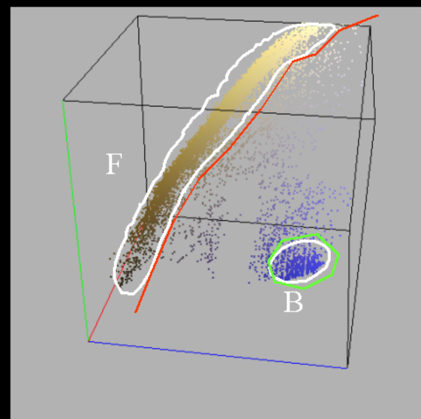
Blue-screen photograph	Spill suppression if B>G then B=G	Matte creation $\bar{\alpha}$=B-max(G,R)

demo with Paint Shop Pro (B=min(B,G))

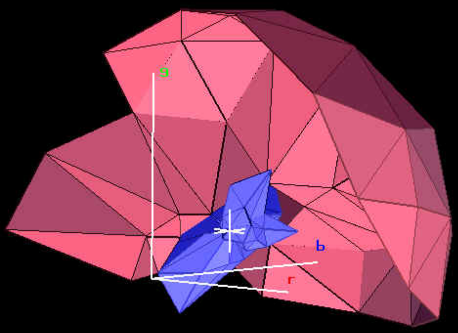
Problems with color difference

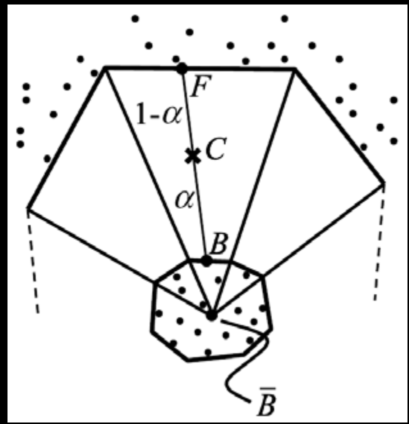
Background color is usually not perfect! (lighting, shadowing…)

Chroma-keying (Primatte)



Chroma-keying (Primatte)





demo

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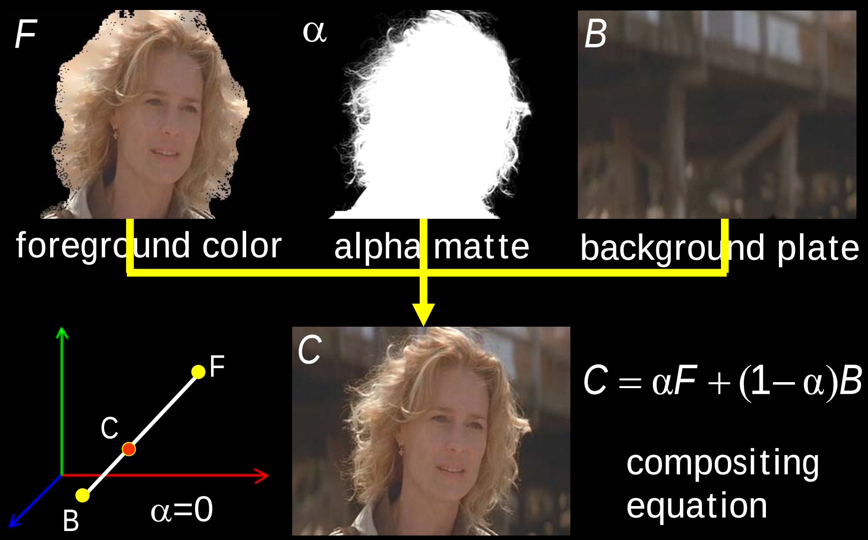
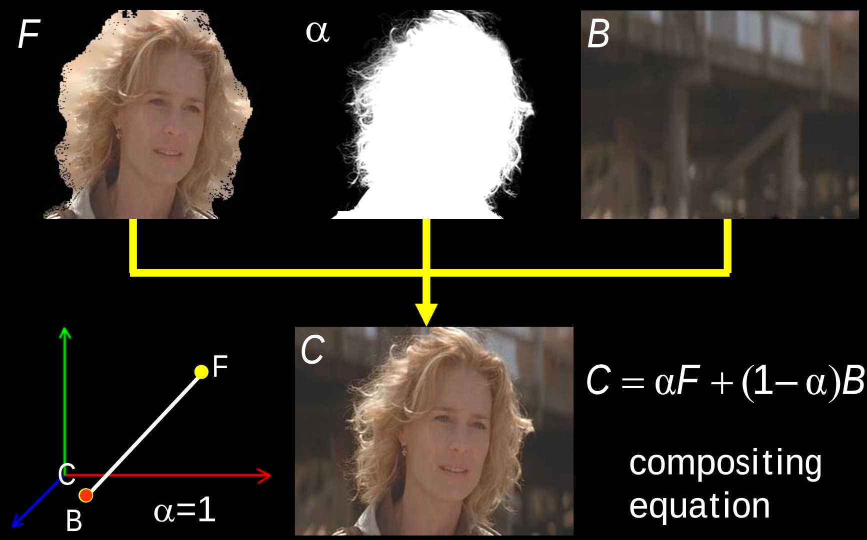
Compositing



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

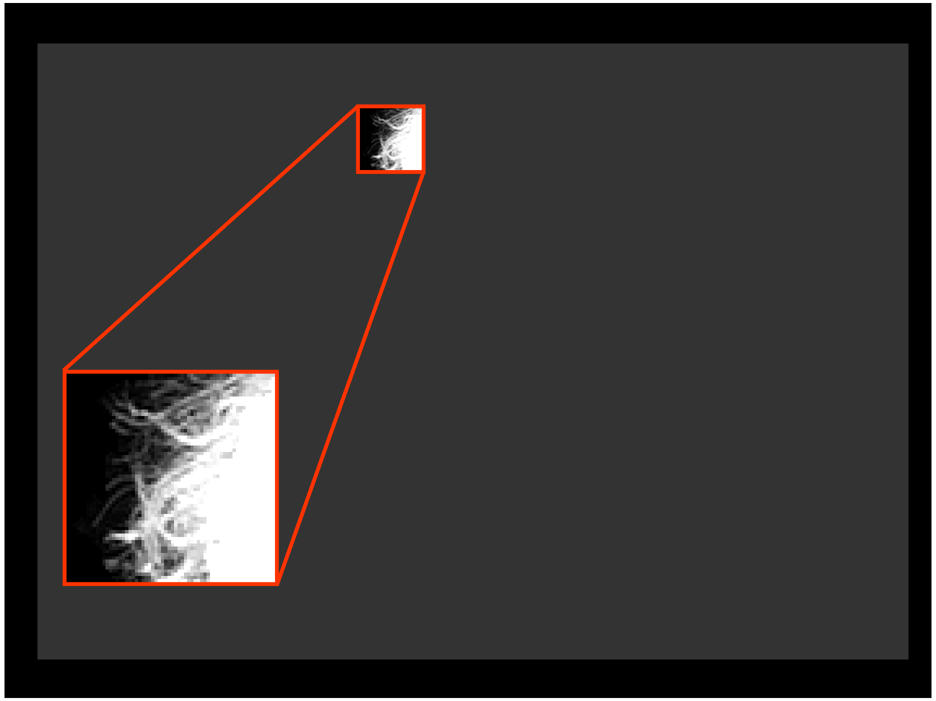
compositing equation

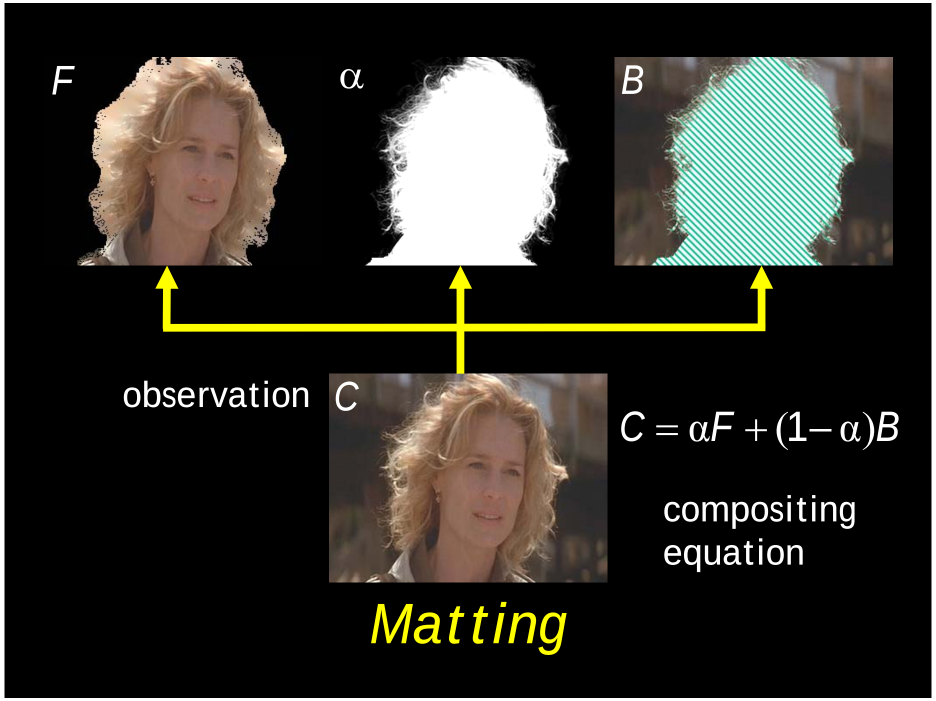
Compositing

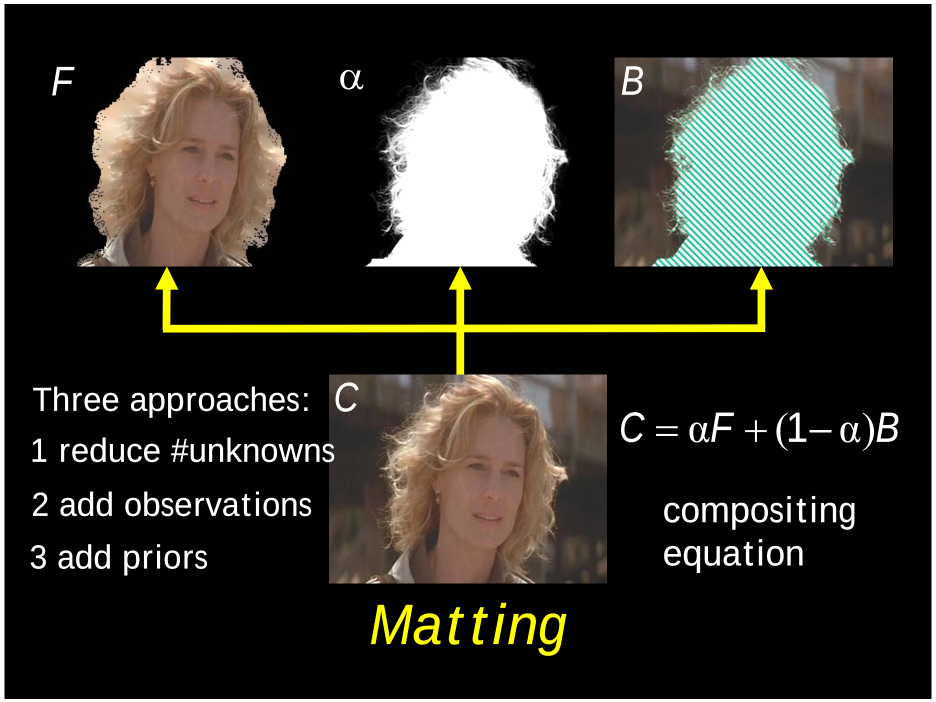


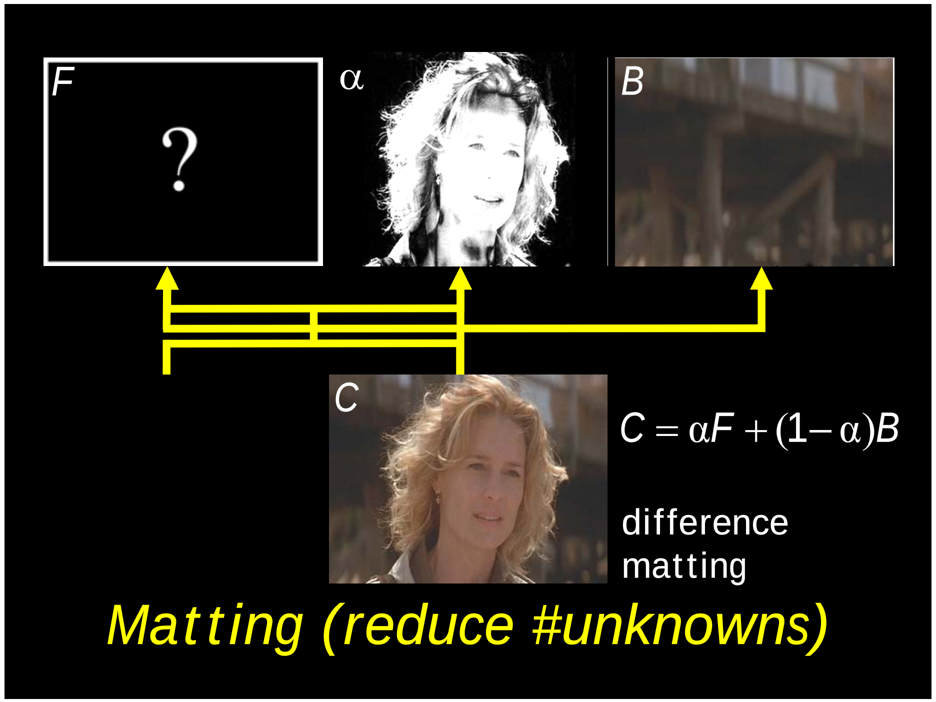
$$C = \alpha F + (1-\alpha) B$$

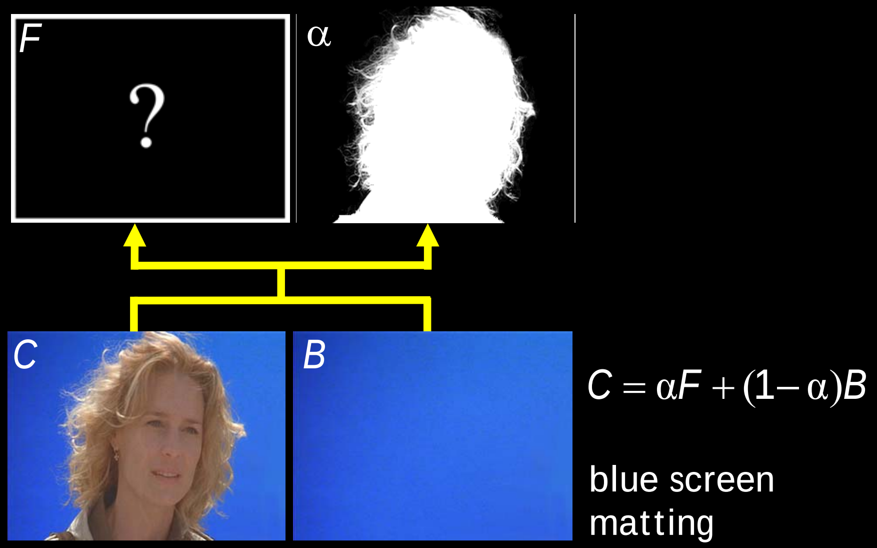
compositing equation



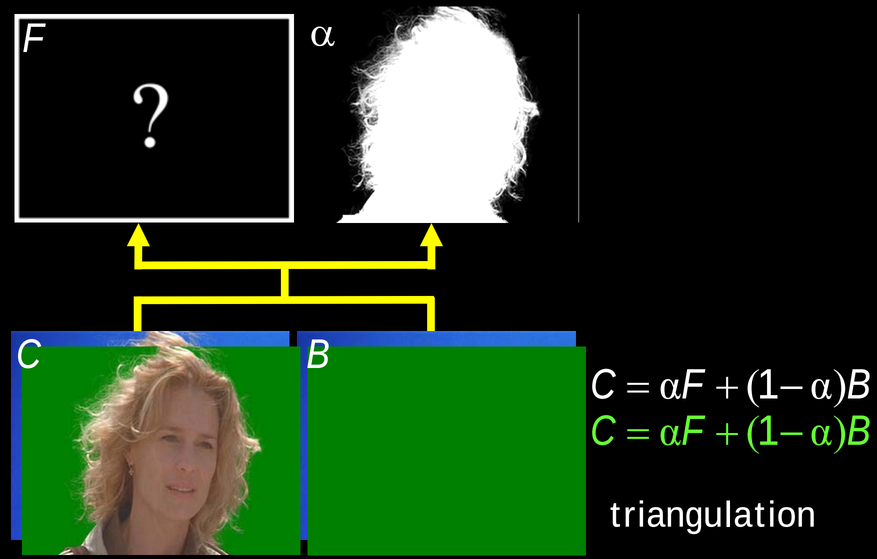

F
α
B
observation
C
$C = \alpha F + (1-\alpha)B$
compositing equation
Matting


F
α
B
Three approaches:
1 reduce #unknowns
2 add observations
3 add priors
C
$C = \alpha F + (1-\alpha)B$
compositing equation
Matting

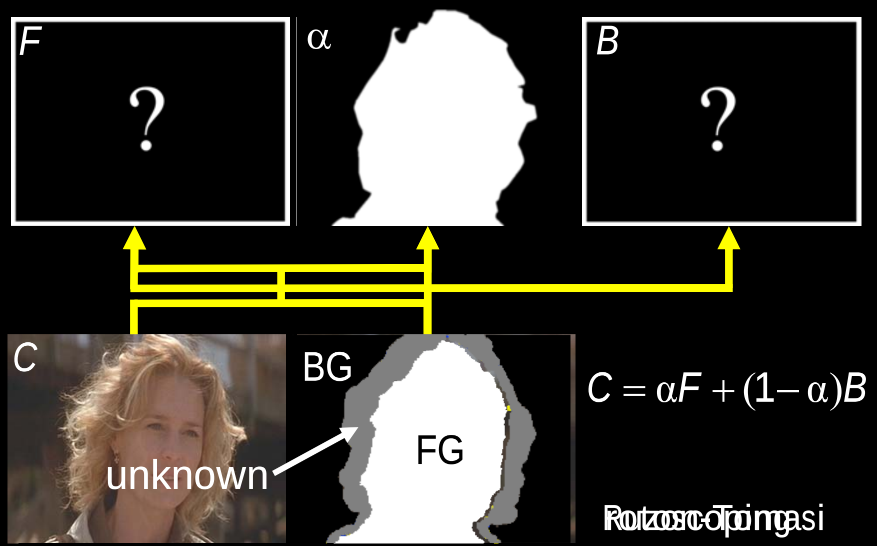

F
?
α
B
C
$C = \alpha F + (1-\alpha)B$
difference matting
Matting (reduce #unknowns)



Matting (reduce #unknowns)



Matting (add observations)



Matting (add priors)

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para-meters z → f(z)+ε → y observed signal

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

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

Bayesian framework

para-meters z → f(z)+ε → y observed signal

$$z^* = \max_z L(y \mid z) + L(z)$$

data evidence $\frac{\|y - f(z)\|^2}{\sigma^2}$

a-priori knowledge

Bayesian framework

posterior probability

likelihood

priors

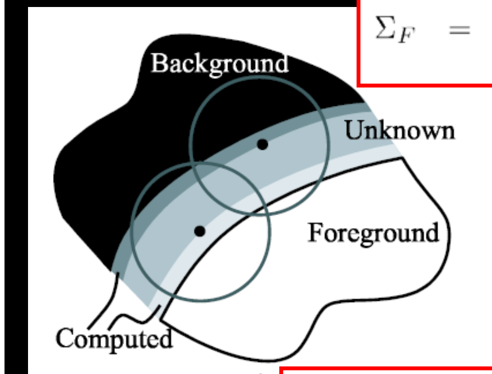
$$\arg\max_{F,B,\alpha} P(F, B, \alpha \mid C) = \arg\max_{F,B,\alpha} P(C \mid F, B, \alpha) P(F) P(B) P(\alpha) / P(C)$$

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

Bayesian framework

$$\overline{F} = \frac{1}{W} \sum_{i \in N} w_i F_i$$

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



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

Priors

$$\arg\max_{F,B,\alpha} L(C \mid F,B,\alpha) + L(F) + L(B)$$

$$\arg\max_{F,B,\alpha} -\|C - \alpha F - (1-\alpha)B\|^2/\sigma_C^2 \\ -(F-\overline{F})^T\,\Sigma_F^{-1}\,(F-\overline{F})\,/\,2 \\ -(B-\overline{B})^T\,\Sigma_B^{-1}\,(B-\overline{B})\,/\,2$$

Bayesian matting

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

Optimization

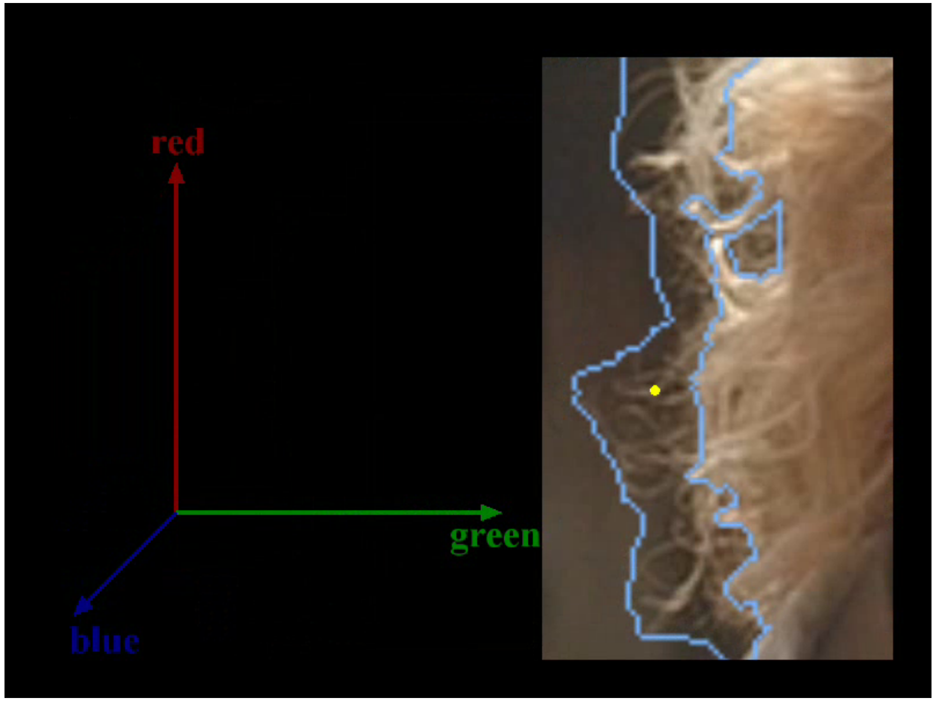
Bayesian image matting

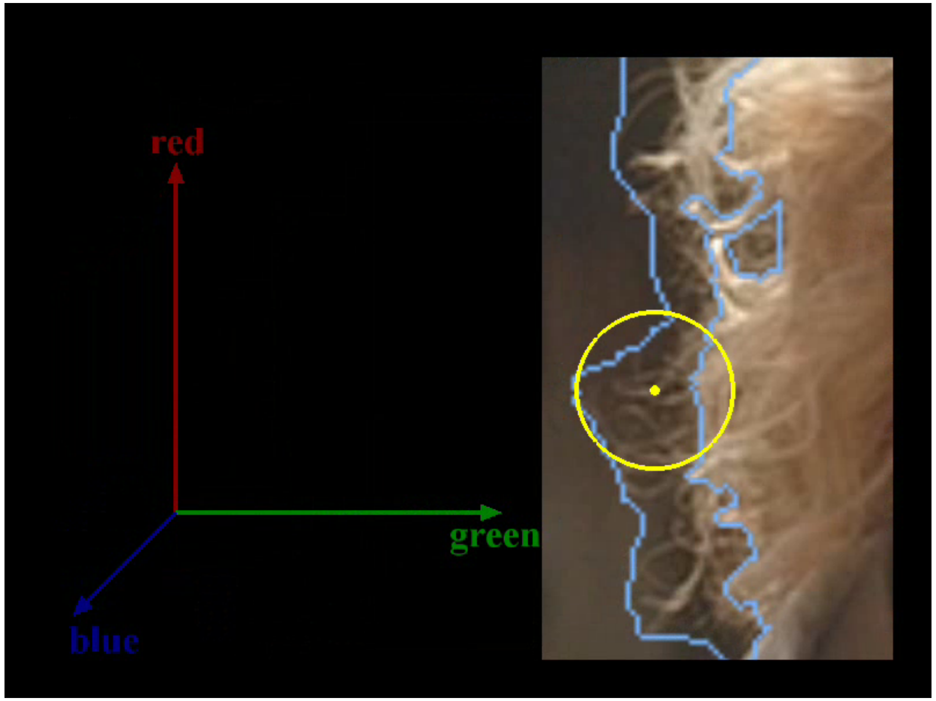
Bayesian image matting

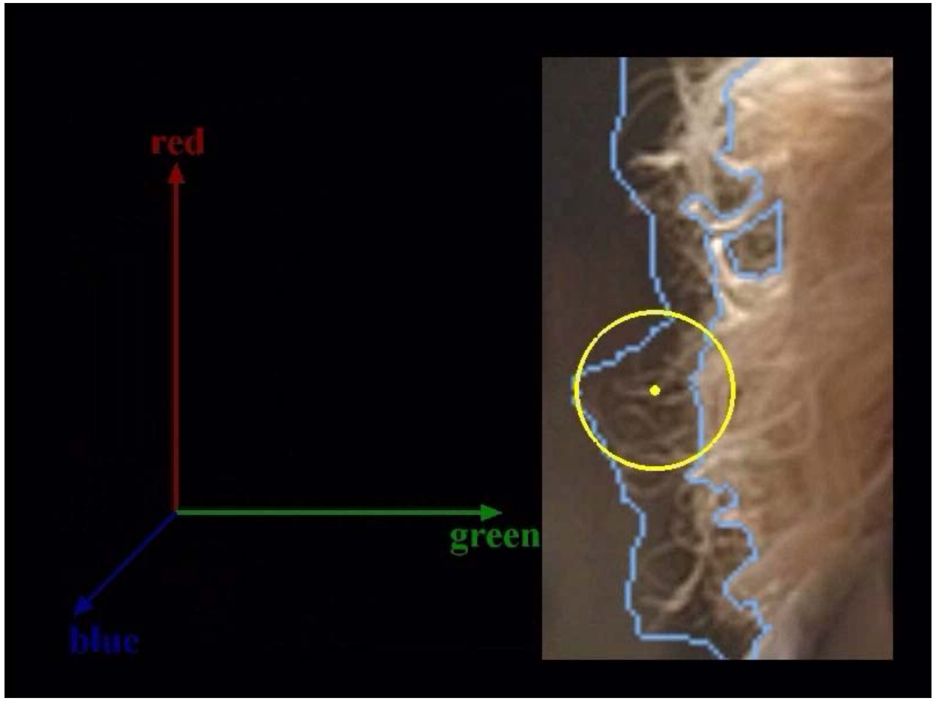

Bayesian image matting

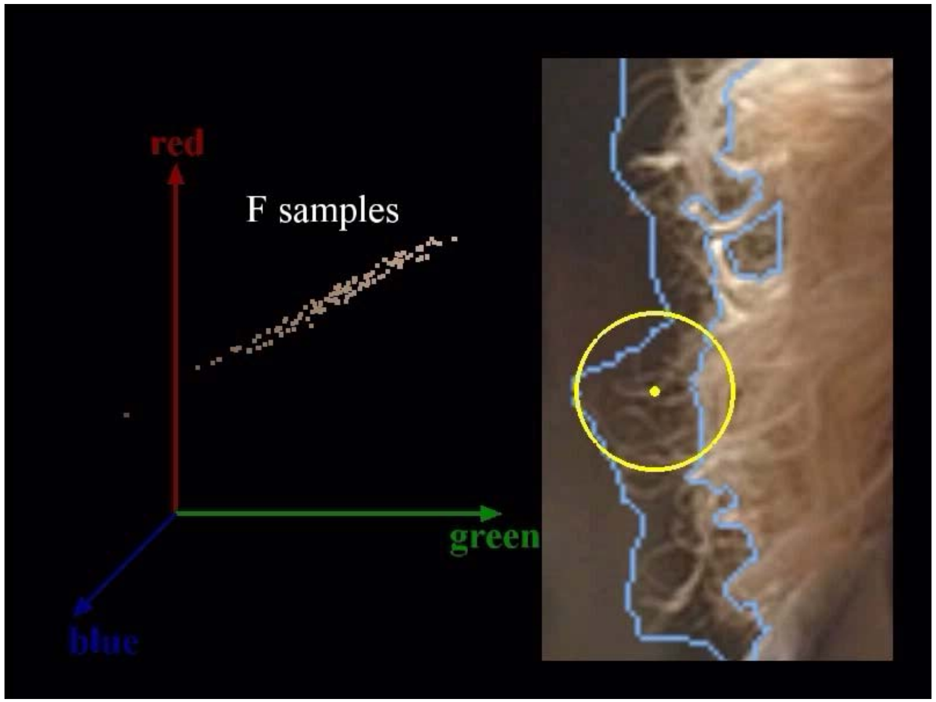

Bayesian image matting

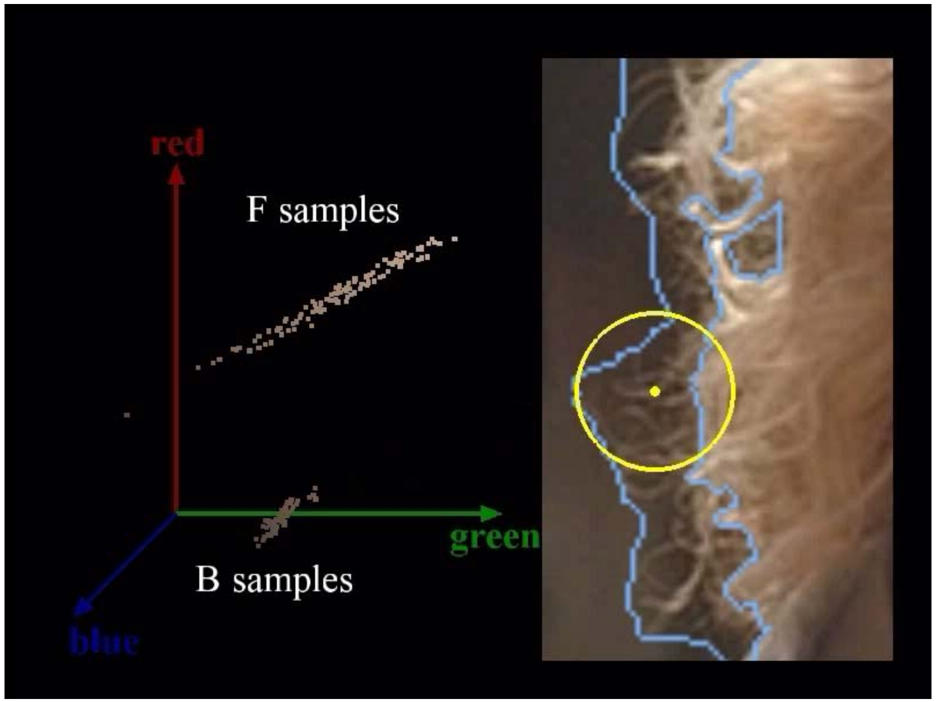

Bayesian image matting

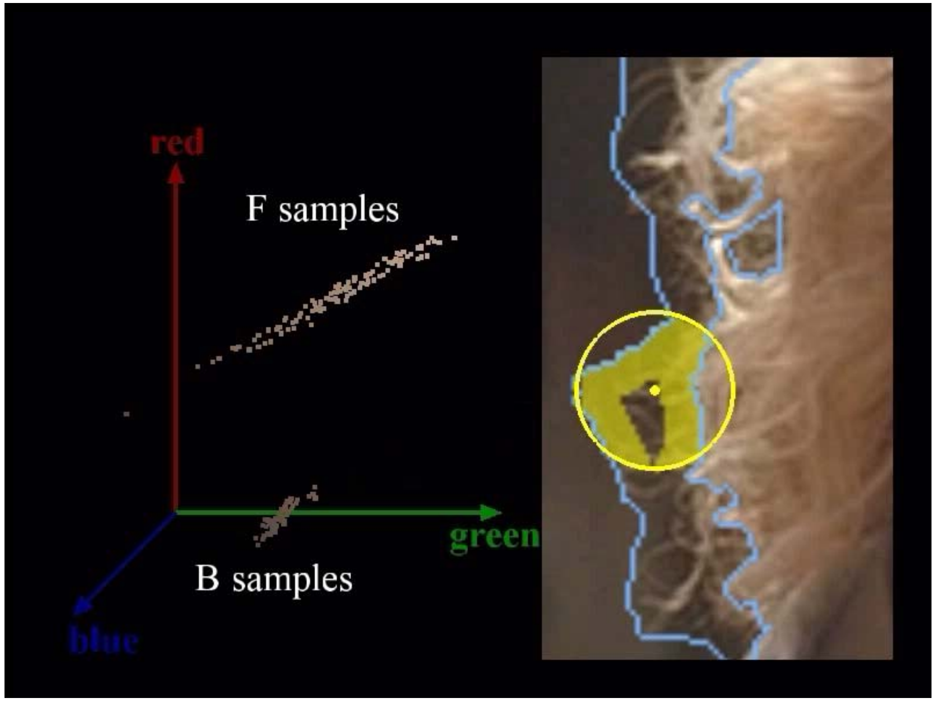

red
green
blue

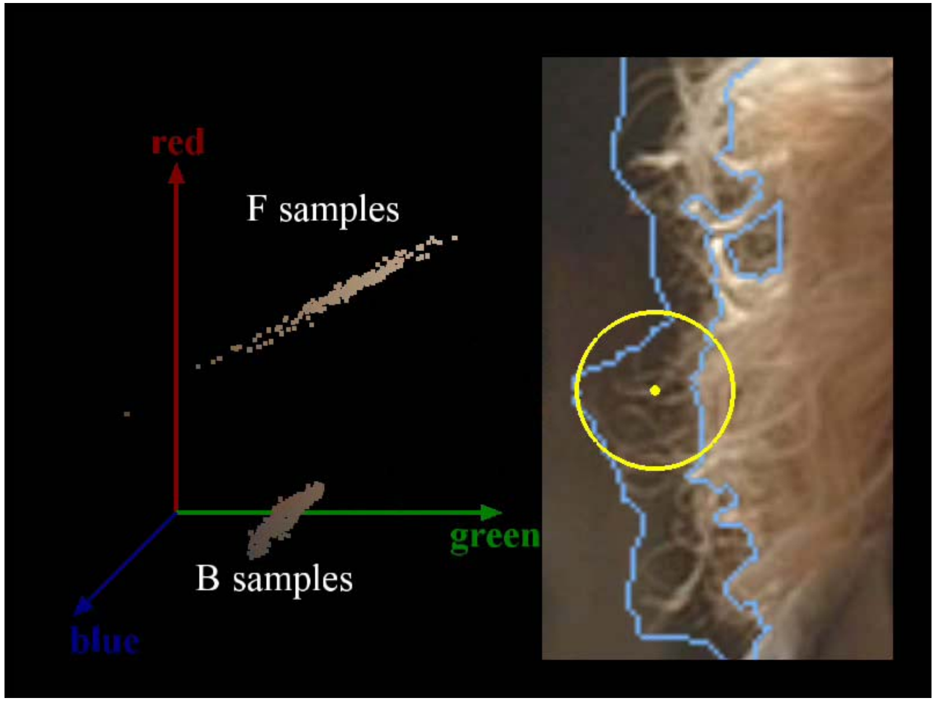

red
green
blue

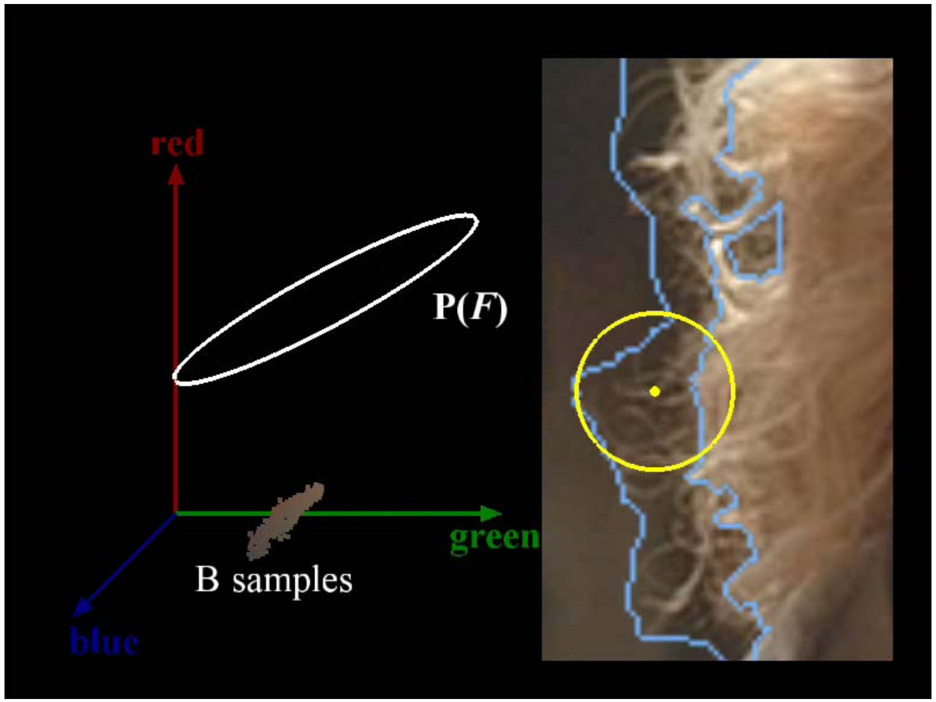

red
green
blue

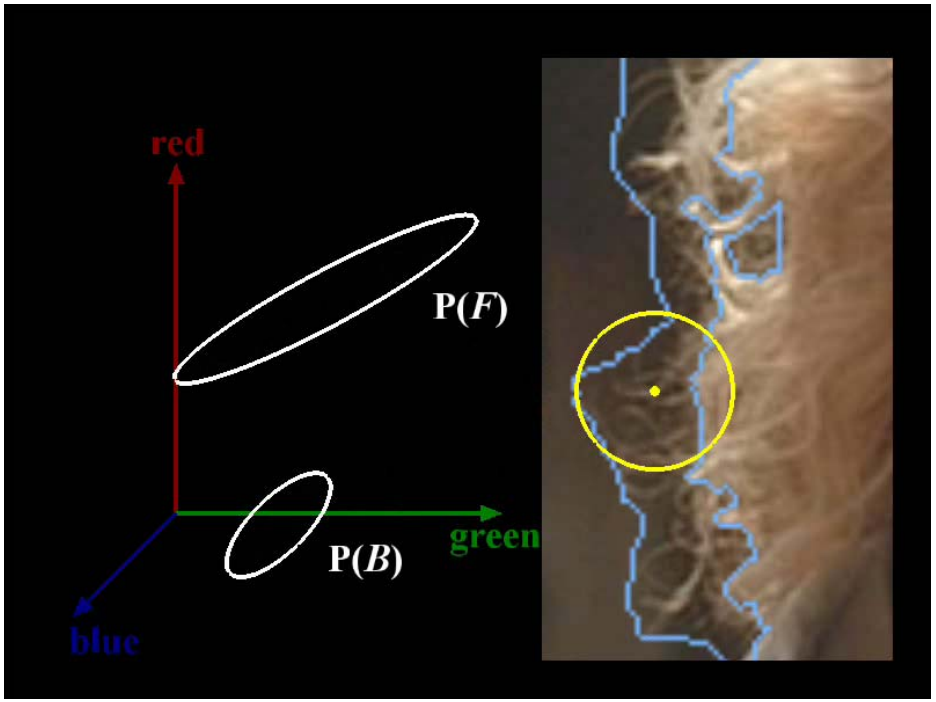

red
F samples
green
blue

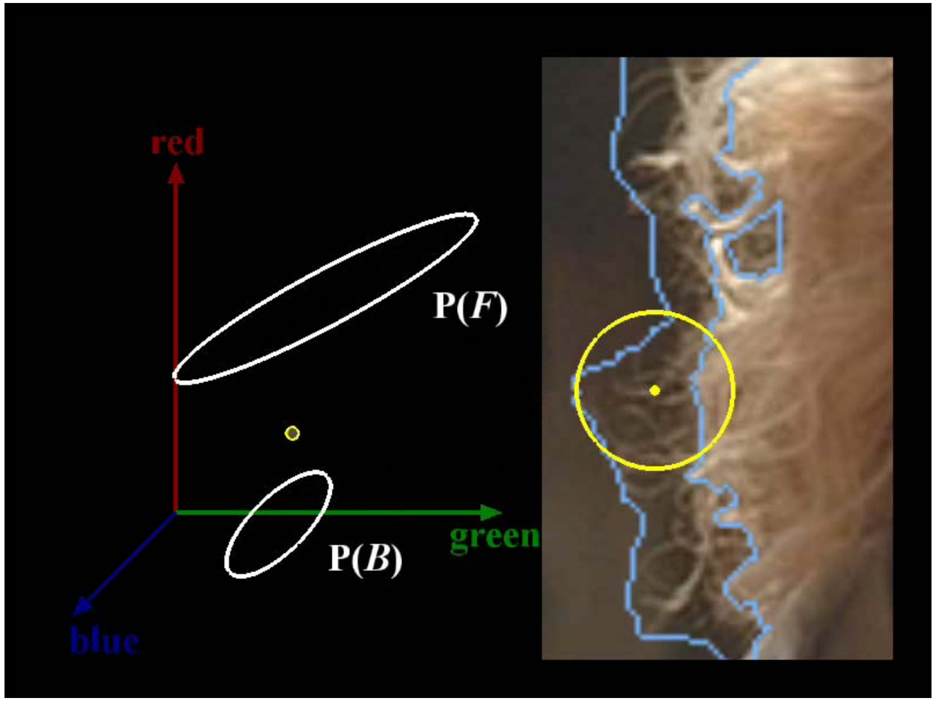

red
F samples
green
B samples
blue

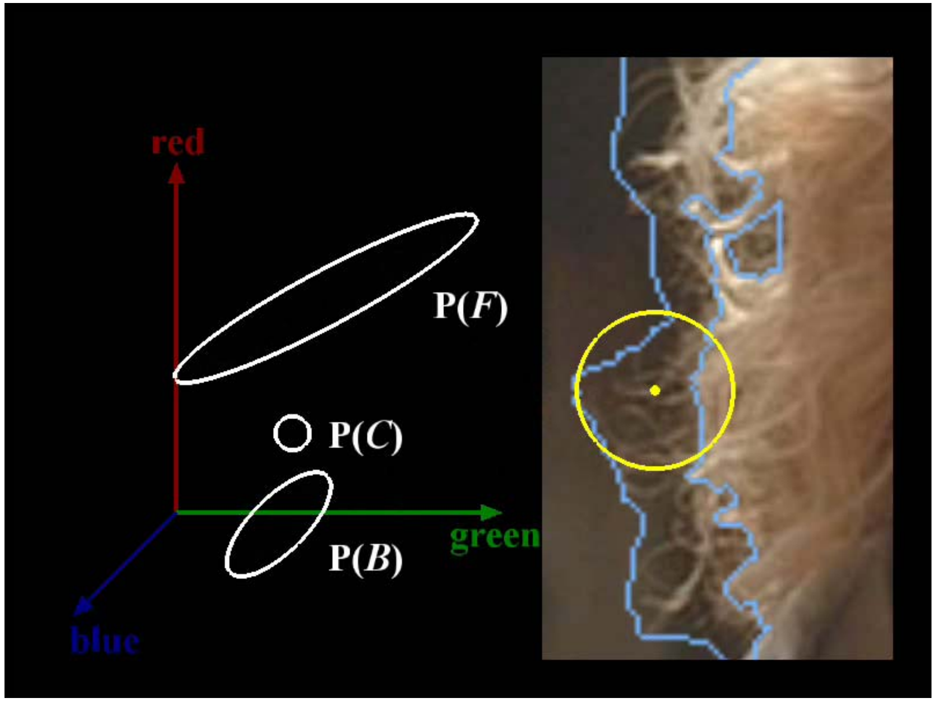

red
F samples
green
B samples
blue

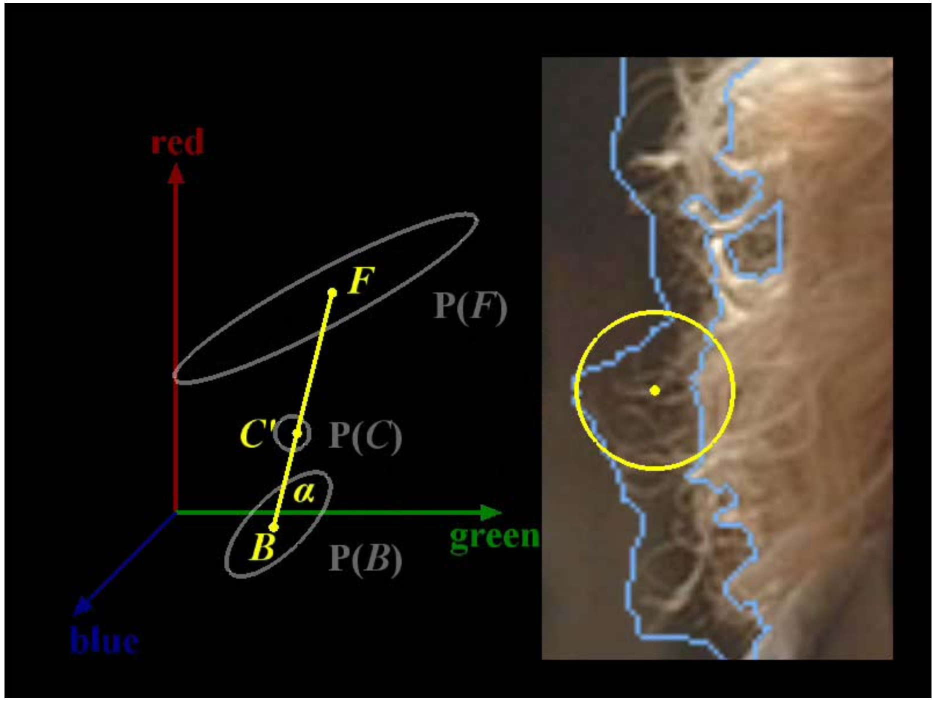

red
F samples
green
B samples
blue


red
P(F)
green
B samples
blue


red
P(F)
green
P(B)
blue


red
P(F)
green
P(B)
blue


red
P(F)
P(C)
green
P(B)
blue

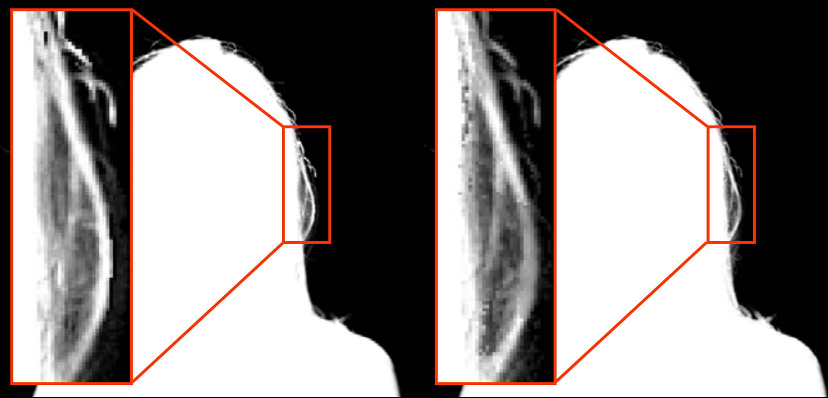

red
F
P(F)
C'
P(C)
α
green
B
P(B)
blue


Demo

Results

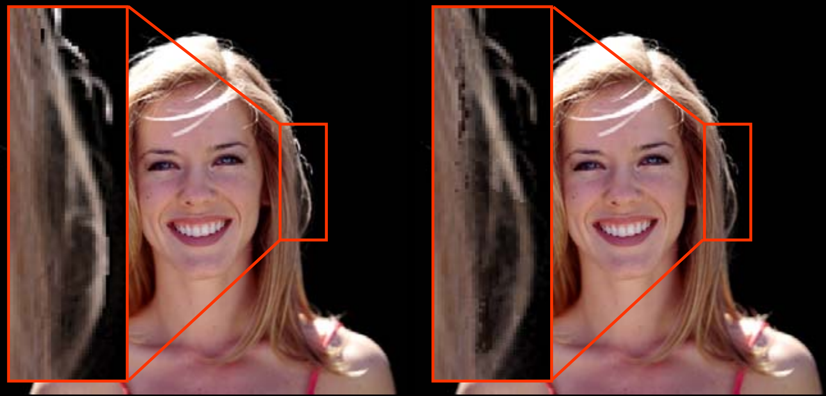
Results

Comparisons



Comparisons

Bayesian Ruzon-Tomasi



Comparisons

Mishima

Comparisons

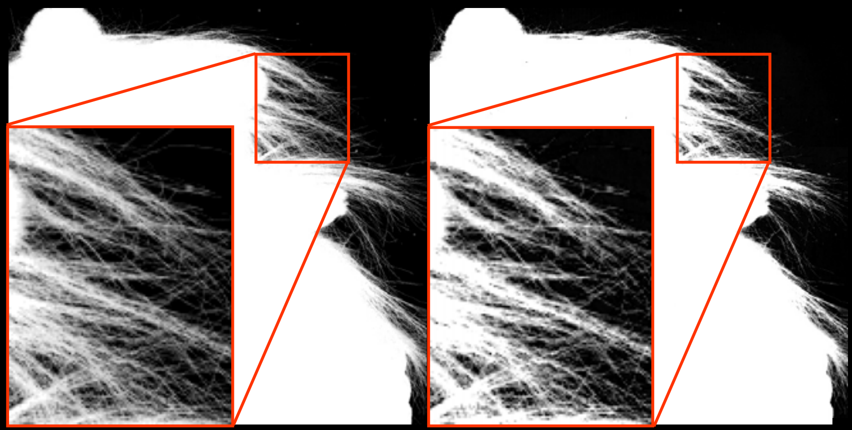
Bayesian

Comparisons

input image

Comparisons

Bayesian Mishima



Comparisons

Bayesian Mishima

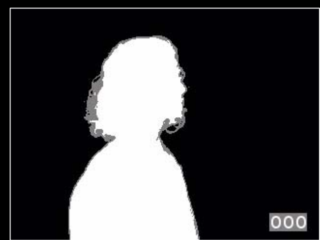
Comparisons

input video

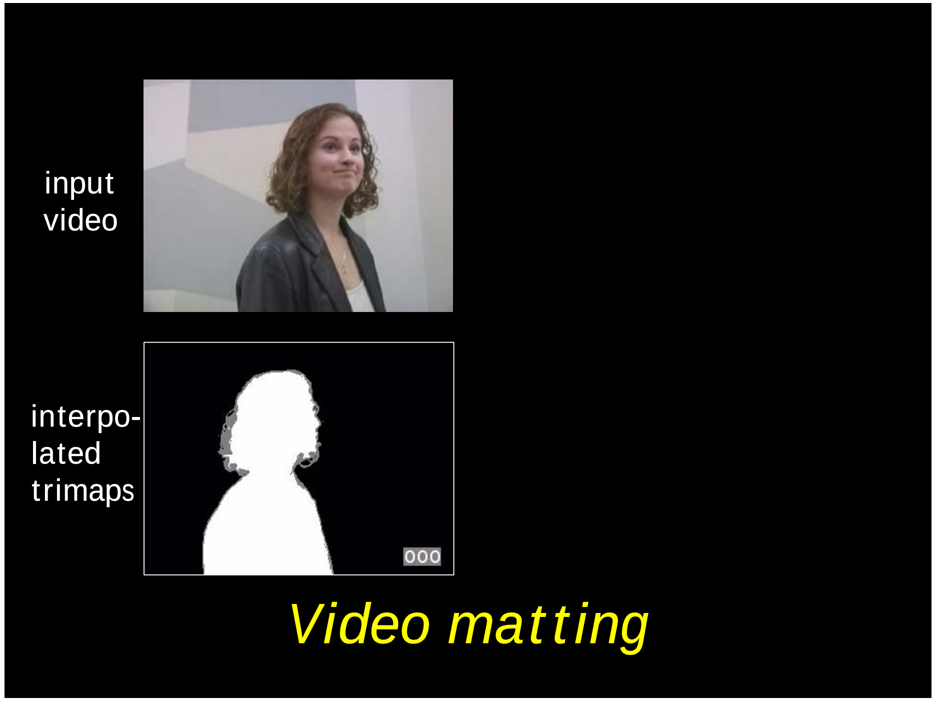
Video matting

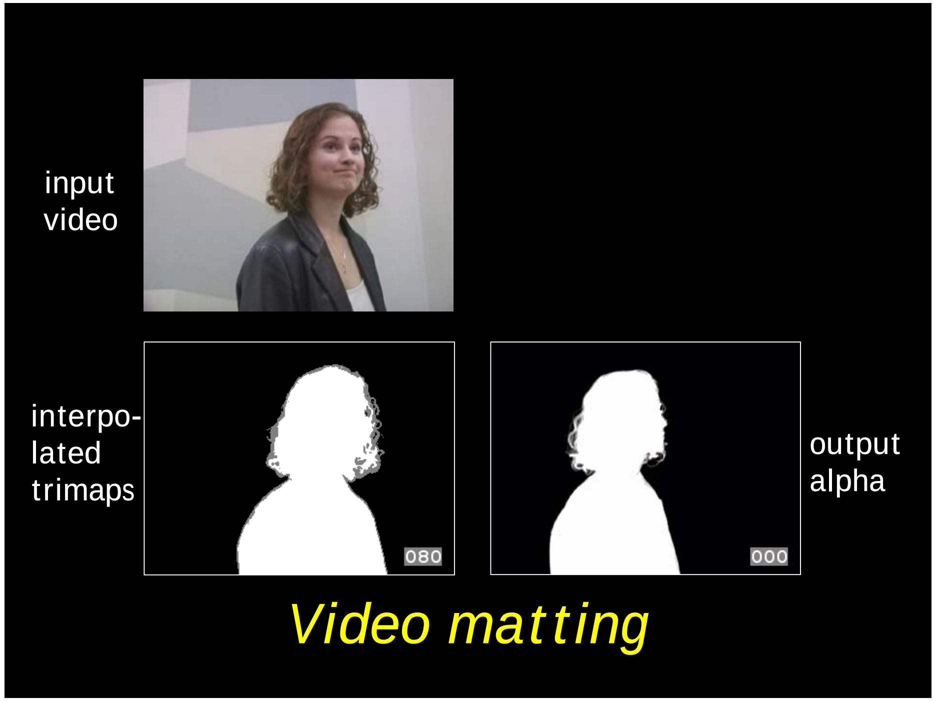
input video

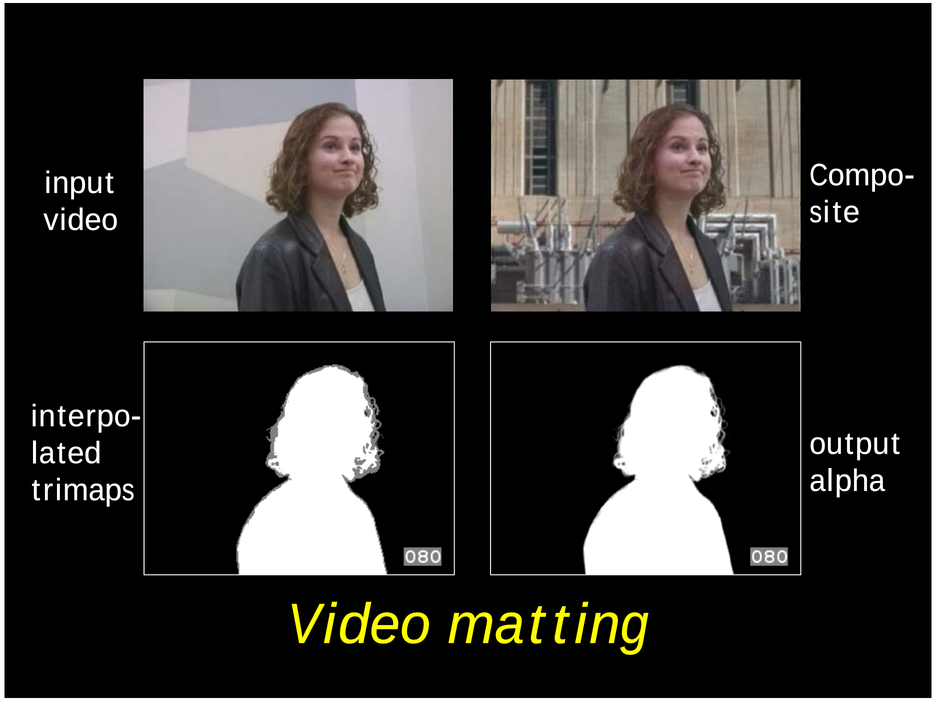
input key trimaps

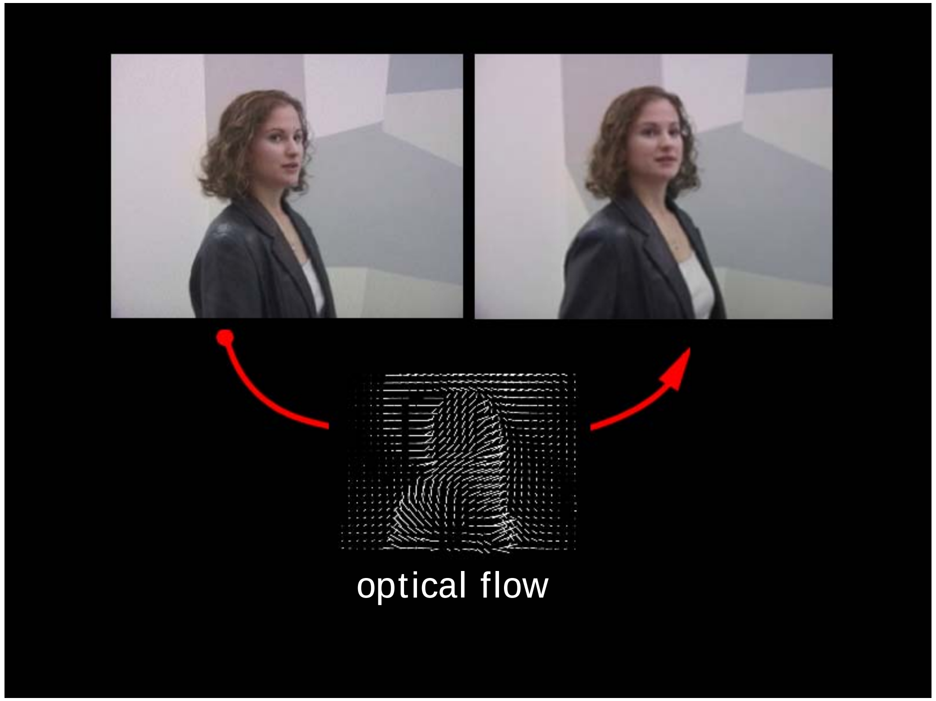


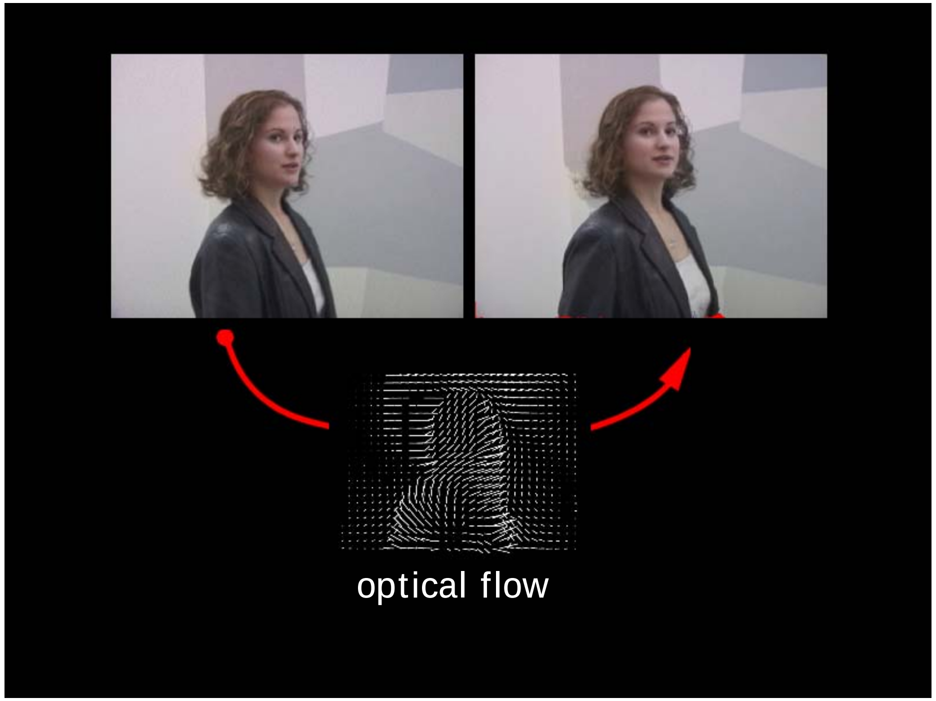
Video matting


input video
interpo-lated trimaps
000
Video matting


input video
interpo-lated trimaps
080
000
output alpha
Video matting

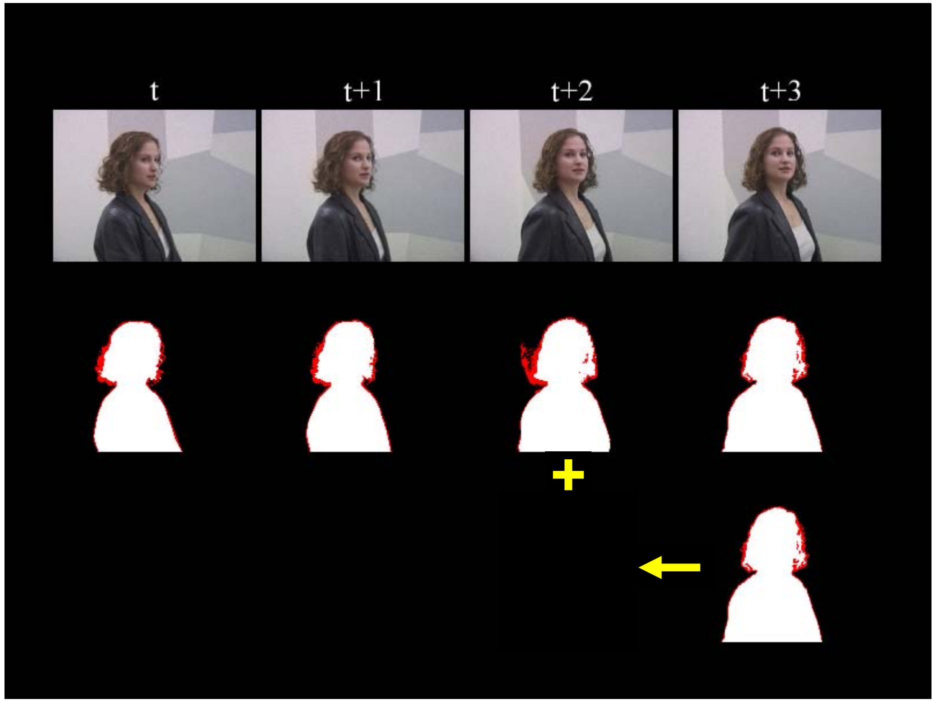

input video
Compo-site
interpo-lated trimaps
080
080
output alpha
Video matting


optical flow


optical flow


t
t+1
t+2
t+3

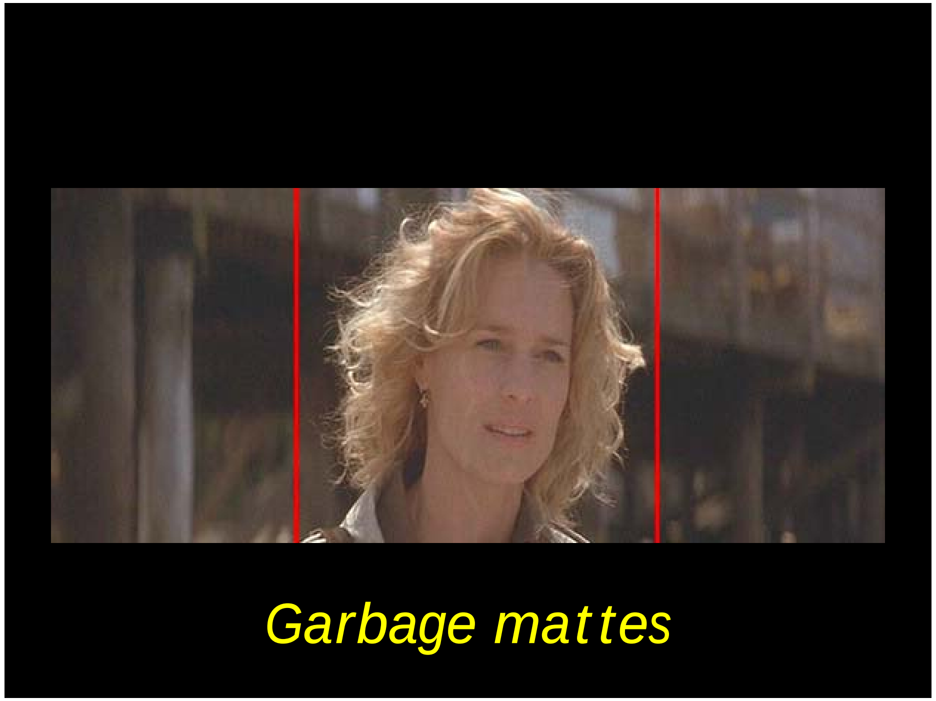

t
t+1
t+2
t+3


t
t+1
t+2
t+3


t
t+1
t+2
t+3


t
t+1
t+2
t+3


Sample composite


Garbage mattes

Garbage mattes

Background estimation

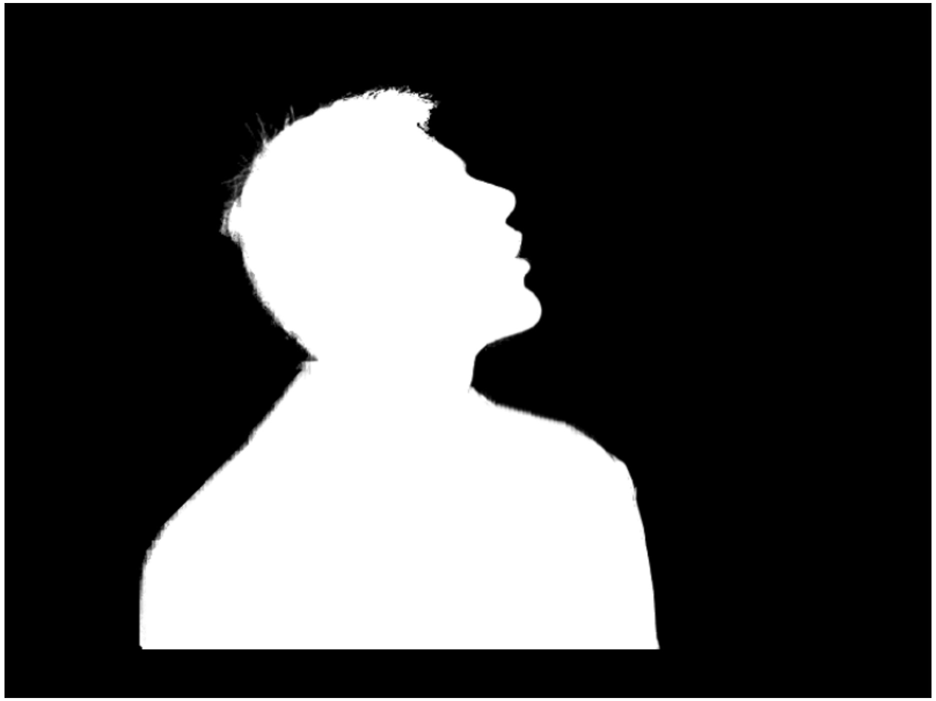
Background estimation

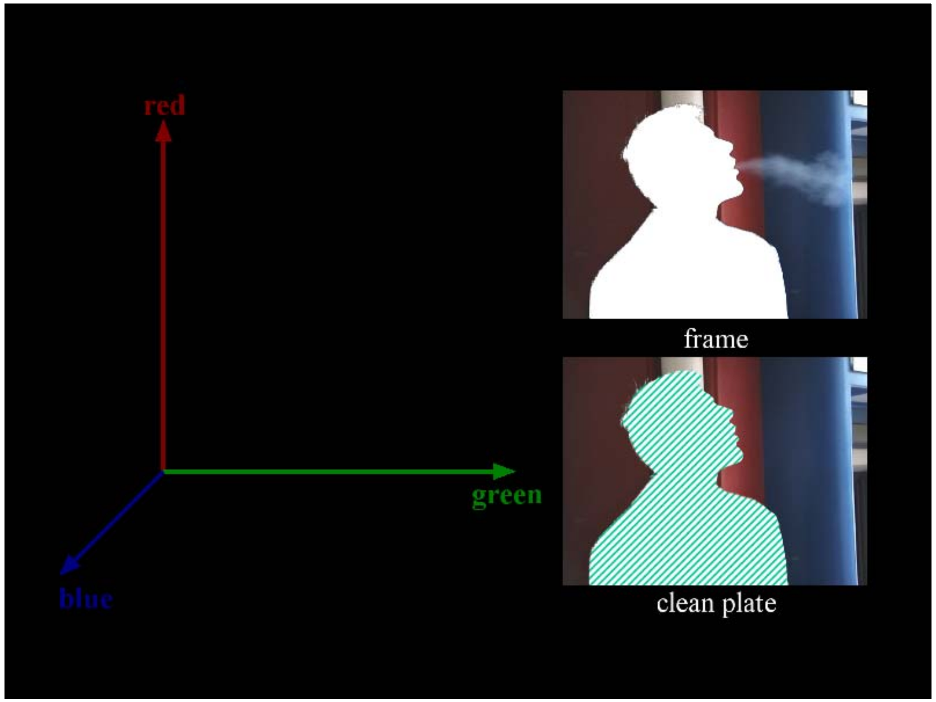
Alpha matte

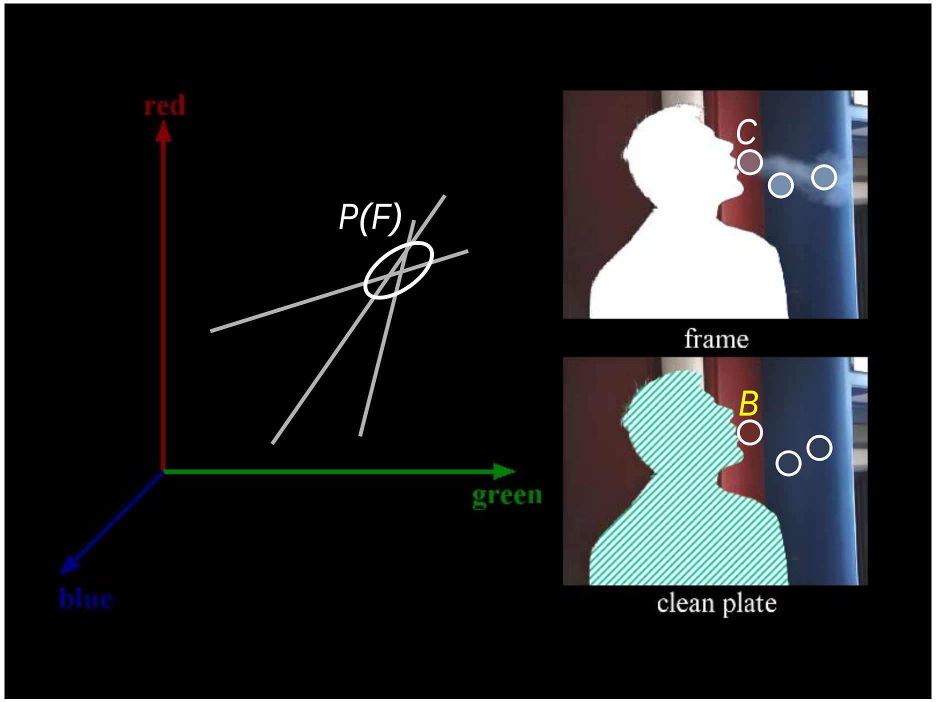
without background

with background

Comparison




red
green
blue
frame
clean plate


red
green
blue
P(F)
C
B
frame
clean plate

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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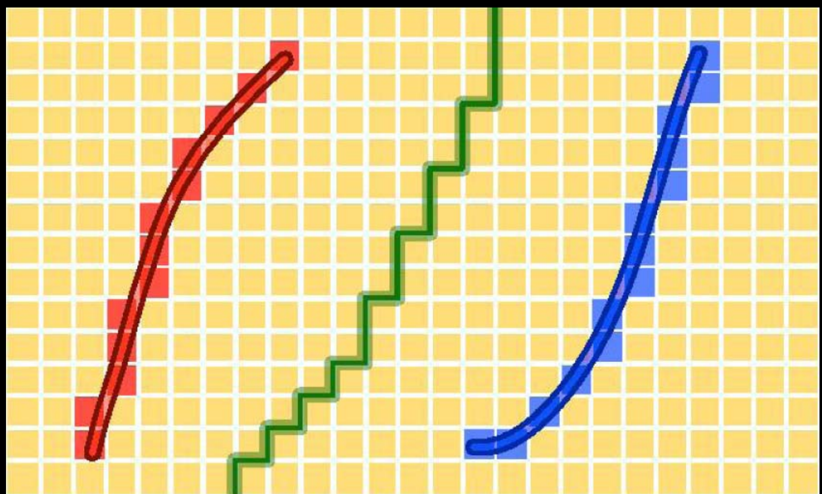
Motivation

LazySnapping



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

$$\begin{array}{llll} E_1(x_i = 1) = 0 & E_1(x_i = 0) = \infty & \forall i \in \mathcal{F} \\ E_1(x_i = 1) = \infty & E_1(x_i = 0) = 0 & \forall i \in \mathcal{B} \\ E_1(x_i = 1) = \frac{d_i^{\mathcal{F}}}{d_i^{\mathcal{F}} + d_i^{\mathcal{B}}} & E_1(x_i = 0) = \frac{d_i^{\mathcal{B}}}{d_i^{\mathcal{F}} + d_i^{\mathcal{B}}} & \forall i \in \mathcal{U} \end{array}$$

LazySnapping

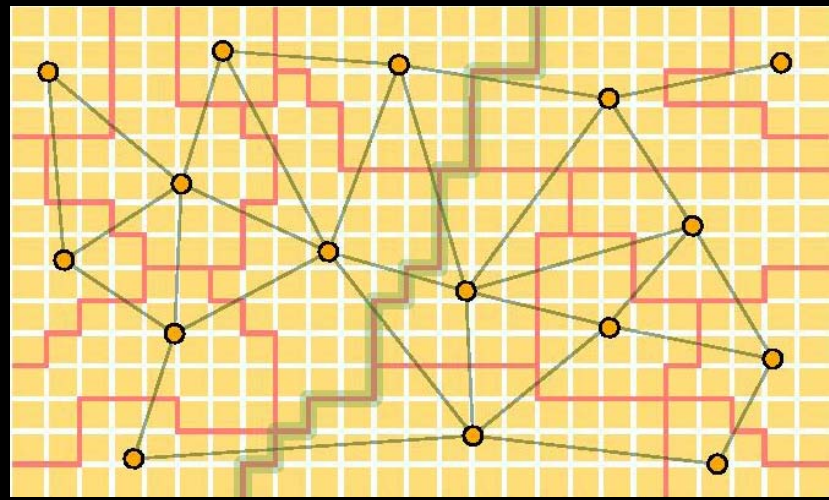
$$E(X) = \sum_{i \in \mathcal{V}} E_1(x_i) + \lambda \sum_{(i,j) \in \mathcal{E}} E_2(x_i, x_j)$$

$$E_2(x_i,x_j) = |x_i - x_j| \cdot g(C_{ij})$$

$$C_{ij} = ||C(i) - C(j)||^2$$

$$g(\varepsilon) = \frac{1}{\varepsilon + 1}$$

LazySnapping



LazySnapping

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

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

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

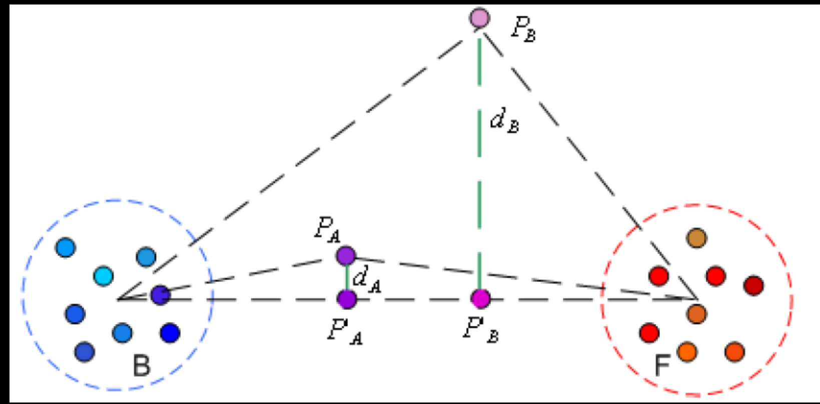
$$\nabla\alpha \approx \frac{1}{F - B}\nabla I$$

$$\alpha^* = \arg\min_{\alpha} \int\int_{p \in \Omega} ||\nabla\alpha_p - \frac{1}{F_p - B_p}\nabla I_p||^2 dp$$

Poisson matting

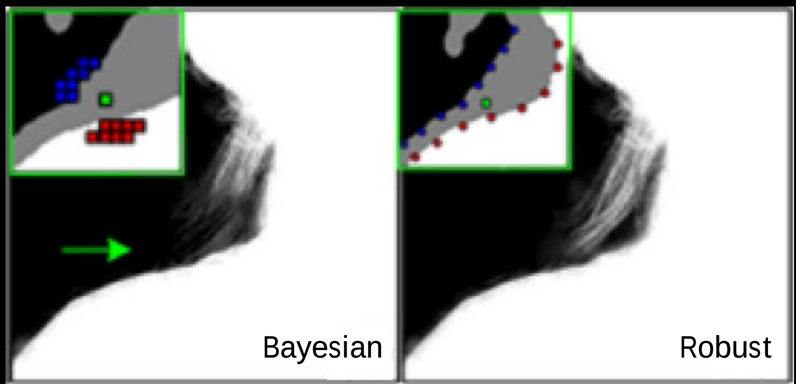
Robust matting

- Jue Wang and Michael Cohen, CVPR 2007



Robust matting

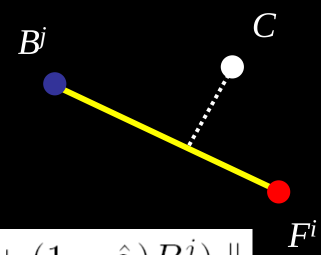
- Instead of fitting models, a non-parametric approach is used



Robust matting

- We must evaluate hypothesized foreground/background pairs

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

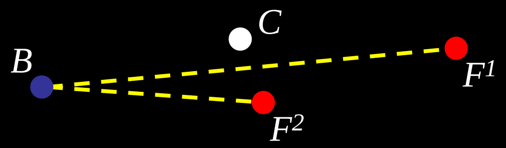


distance ratio

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

Robust matting

- To encourage pure fg/bg pixels, add weights



$$w(F^i) = exp\{- \parallel F^i - C \parallel^2 / D_F^2\}$$

$$\min_i(\parallel F^i - C \parallel)$$

$$w(B^j) = exp\{- \parallel B^j - C \parallel^2 / D_B^2\}$$

$$\min_j(\parallel B^j - C \parallel)$$

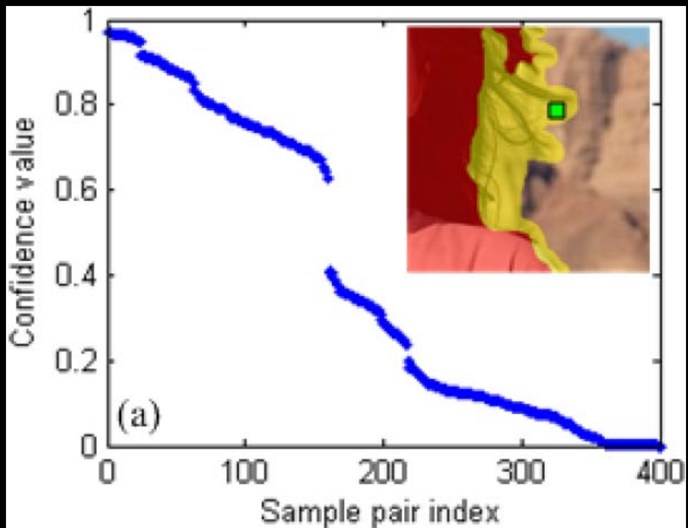
Robust matting

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

confidence

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

Robust matting

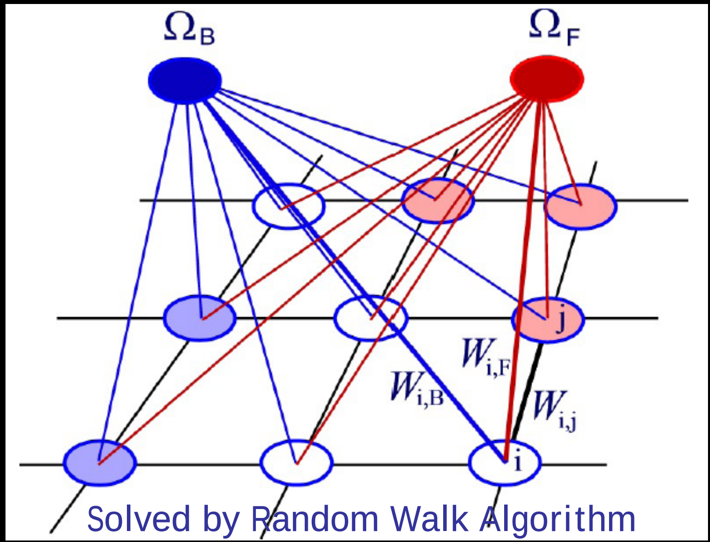


Robust matting

matte

confidence

Matte optimization



Matte optimization

data constraints

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

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

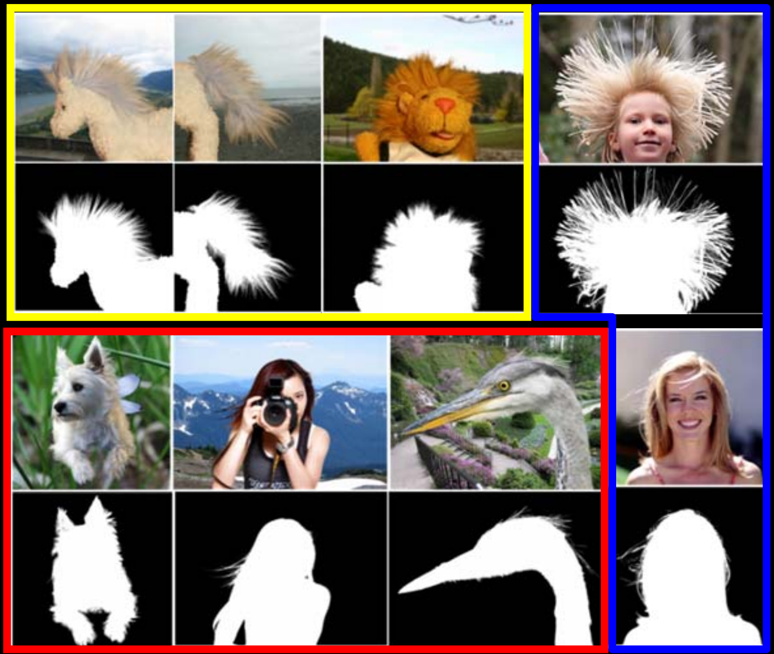
neighborhood constraints

$$W_{ij} = \sum_{k}^{(i,j)\in w_k} \frac{1}{9}(1 + (C_i - \mu_k)(\Sigma_k + \frac{\epsilon}{9} I)^{-1}(C_j - \mu_k))$$

Demo (EZ Mask)

Evaluation

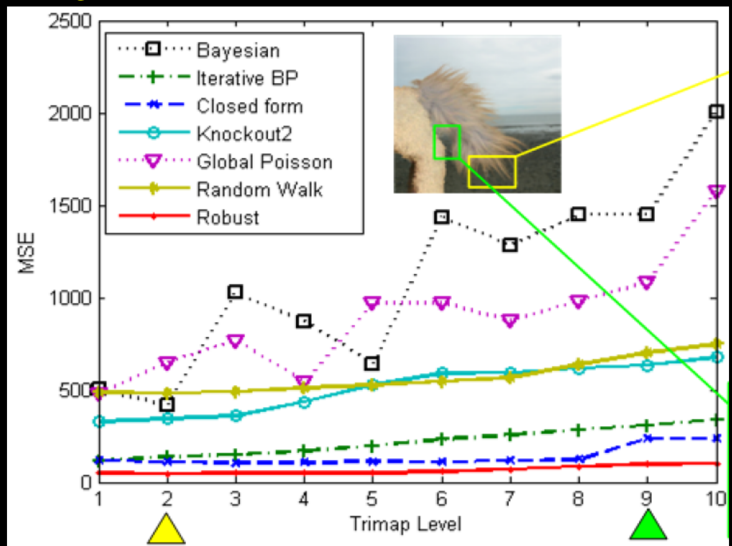
- 8 images collected in 3 different ways
- Each has a “ground truth” matte



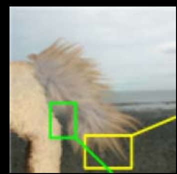
Evaluation

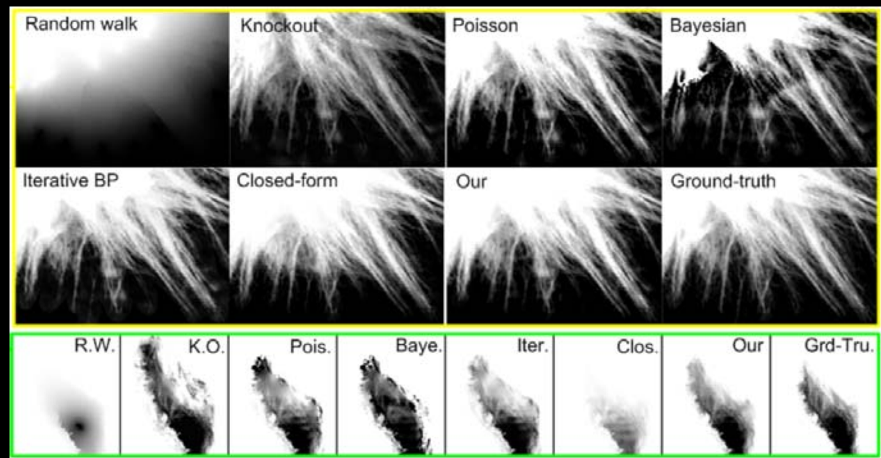
- Mean square error is used as the accuracy metric
- Try 8 trimaps with different accuracy for testing robustness
- 7 methods are tested: Bayesian, Belief propagation, Poisson, Random Walk, KnockOut2, Closed-Form and Robust matting

Quantitative evaluation

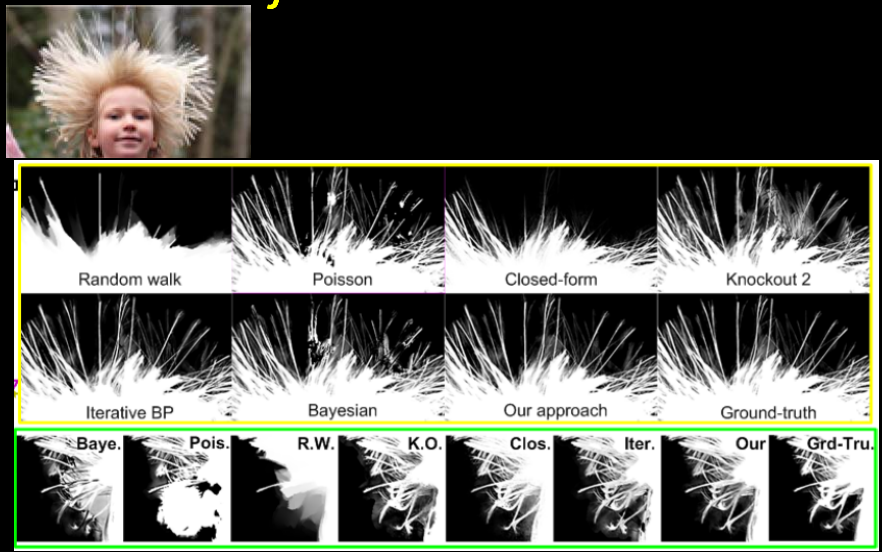


Subjective evaluation





Subjective evaluation



Ranks of these algorithms

	accuracy	robustness
Poisson	6.9	6.8
Random walk	6.0	4.4
Knockout2	4.5	4.5
Bayesian	3.9	6.0
Belief Propagation	3.3	3.1
Close-form	2.6	2.0
Robust matting	1.0	1.3

Summary

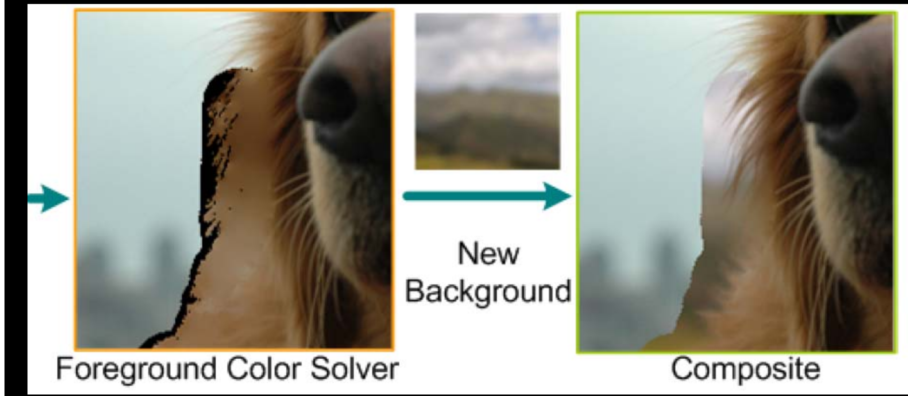
- Propagation-based methods are more robust
- Sampling-based methods often generate more accurate mattes than propagation-based ones with fine trimaps
- Robust matting combines strengths of both

Soft scissor

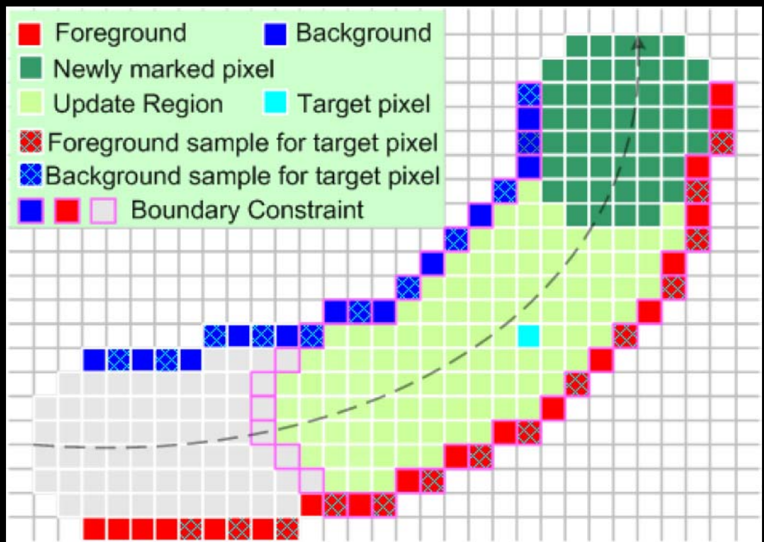
- Jue Wang et. al., SIGGRAPH 2007
- Users interact in a similar way to intelligent scissors

Flowchart

Flowchart



Soft scissor



Demo (Power Mask)

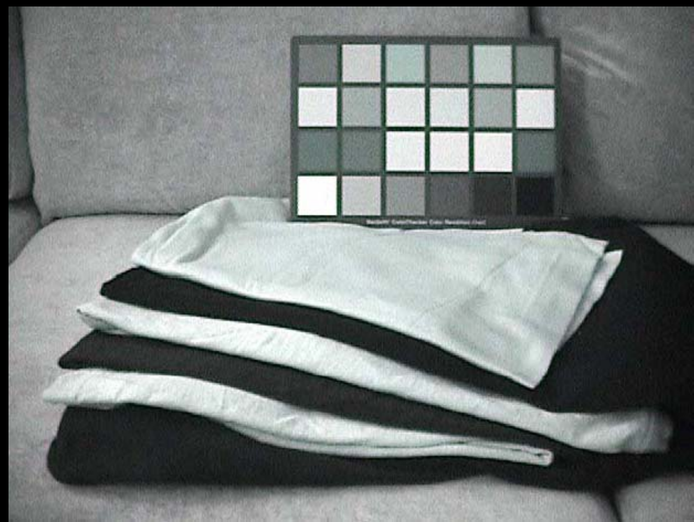
Outline

- 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

Matting with multiple observations

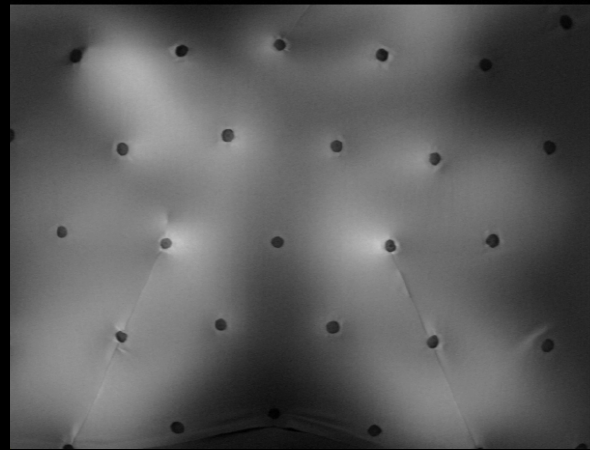
- Invisible lights
  - Polarized lights
  - Infrared
- Thermo-key
- Depth Keying (ZCam)
- Flash matting

Invisible lights (Infared)



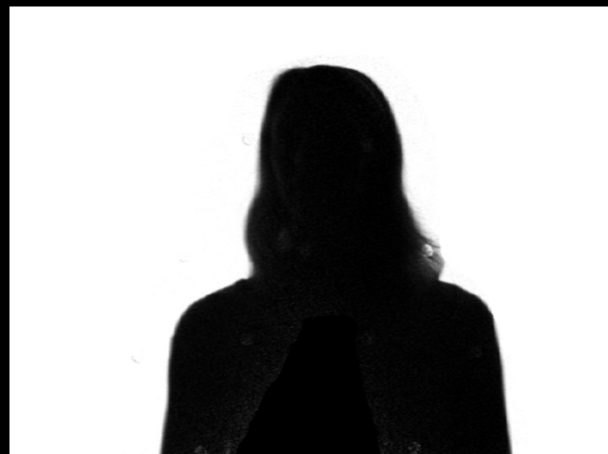
Invisible lights (Infared)

Invisible lights (Infared)

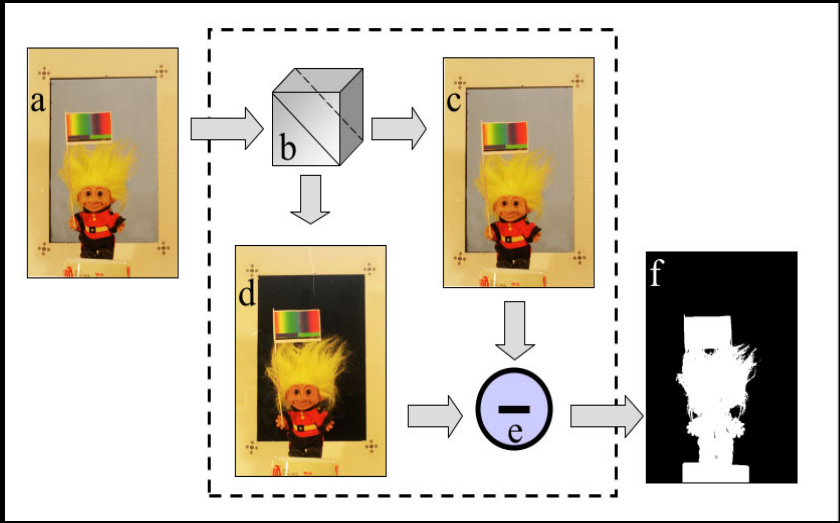


Invisible lights (Infared)

Invisible lights (Infared)

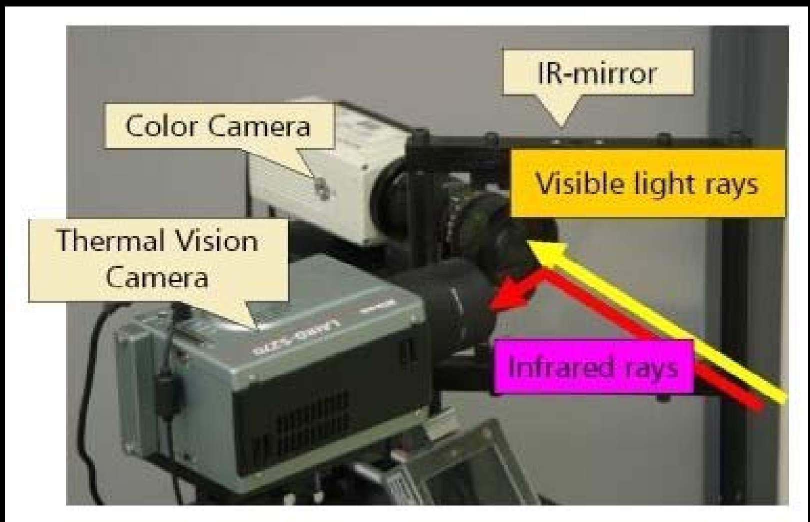


Invisible lights (Infared)

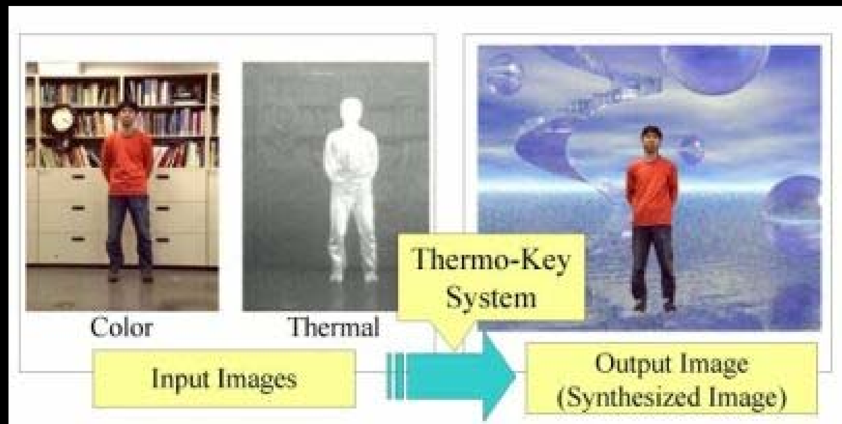


Invisible lights (Polarized)

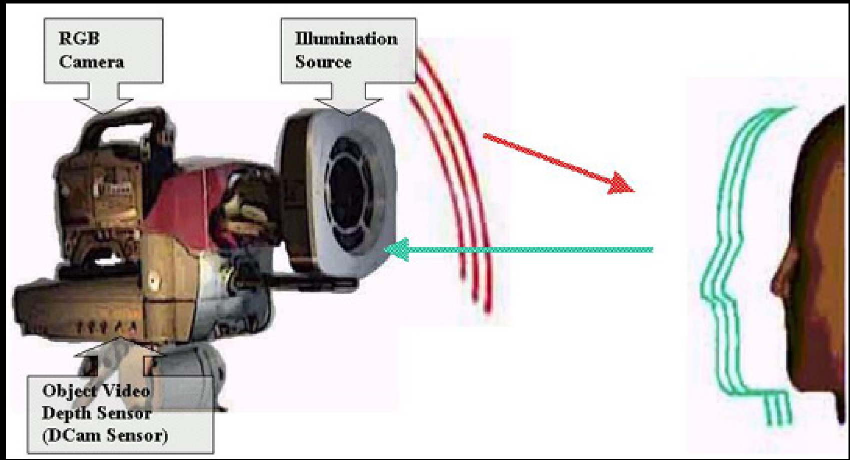
Invisible lights (Polarized)



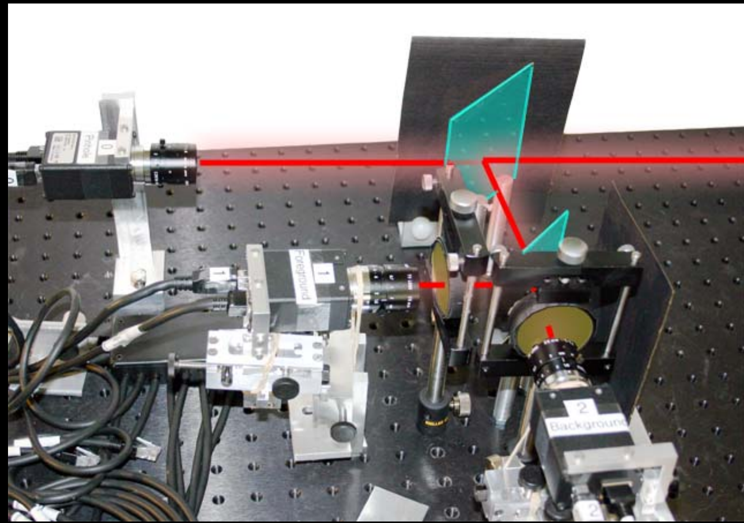
Thermo-Key



Thermo-Key

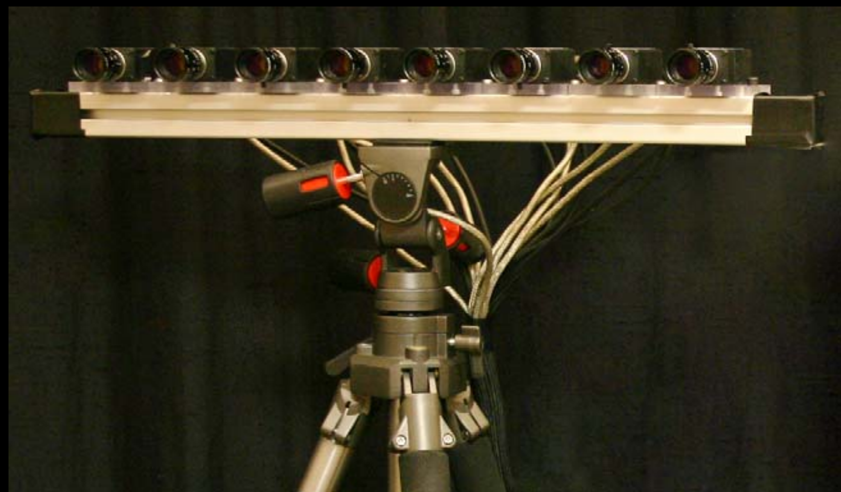


ZCam



Defocus matting

video



video

Matting with camera arrays

flash

no flash

matte

Flash matting

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

Background is much further than foreground and receives almost no flash light $B^f \approx B$

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

Flash matting

Foreground flash matting equation

$$I' = I^f - I = \alpha(F^f - F) = \alpha F'$$

Generate a trimap and directly apply Bayesian matting.

$$\arg\max_{\alpha,F'} L(\alpha, F' | I')$$
$$= \arg\max_{\alpha,F'} \{L(I'|\alpha, F') + L(F') + L(\alpha)\}$$
$$L(I'|\alpha, F') = -||I' - \alpha F'||/\sigma^2_{I'}$$
$$L(F') = -(F' - \overline{F'})^T \Sigma^{-1}_{F'} (F' - \overline{F'})$$

Flash matting

Foreground flash matting

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

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

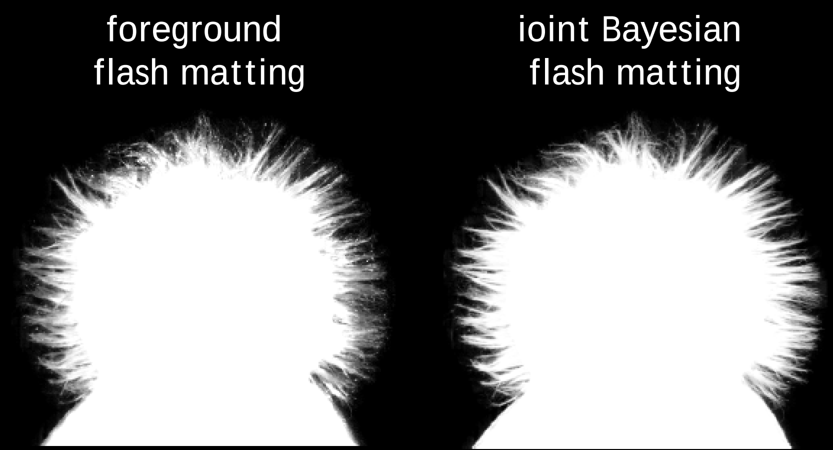
Joint Bayesian flash matting

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

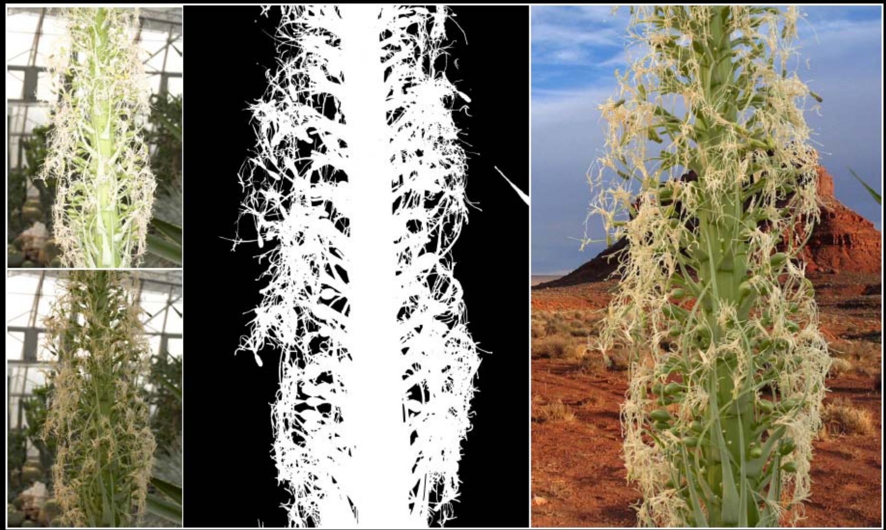
$$\begin{bmatrix} \Sigma_F^{-1} + \mathbf{I}\alpha^2/\sigma_I^2 & \mathbf{I}\alpha(1-\alpha)\sigma_I^2 & \mathbf{0} \\ \mathbf{I}\alpha(1-\alpha)\sigma_I^2 & \Sigma_B^{-1} + \mathbf{I}\alpha^2/\sigma_I^2 & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \Sigma_{F'}^{-1} + \mathbf{I}\alpha^2/\sigma_{I'}^2 \end{bmatrix} \begin{bmatrix} F \\ B \\ F' \end{bmatrix}$$
$$= \begin{bmatrix} \Sigma_F^{-1}\overline{F} + I\alpha/\sigma_I^2 \\ \Sigma_B^{-1}\overline{B} + I(1-\alpha)/\sigma_I^2 \\ \Sigma_{F'}^{-1}\overline{F'} + I'\alpha/\sigma_{I'}^2 \end{bmatrix},$$

Joint Bayesian flash matting

Comparison



Comparison



Flash matting

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Conclusions

- Matting algorithms improves 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