

Matting and Compositing

Digital Visual Effects
Yung-Yu Chuang

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



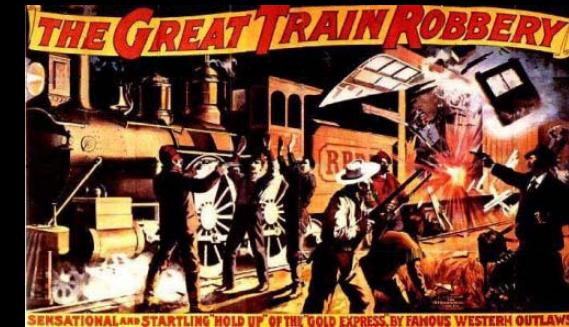
The Two Ways of Life, 1857, Oscar Gustav Rejlander
Printed from the original 32 wet collodion negatives.

Photographic compositions



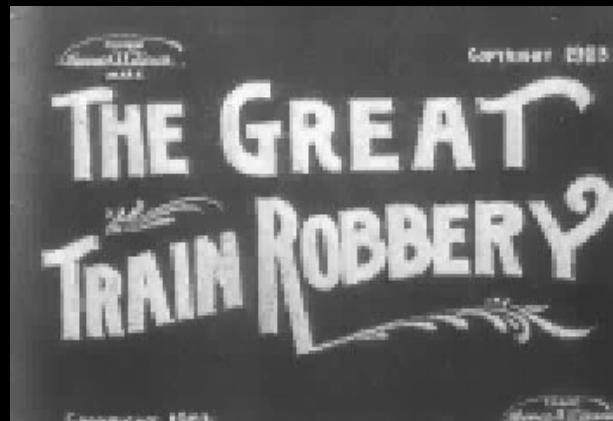
Lang Ching-shan

Use of mattes for compositing



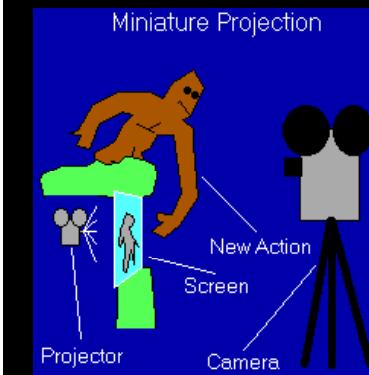
The Great Train Robbery (1903) matte shot

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

Smith Duff Catmull Porter

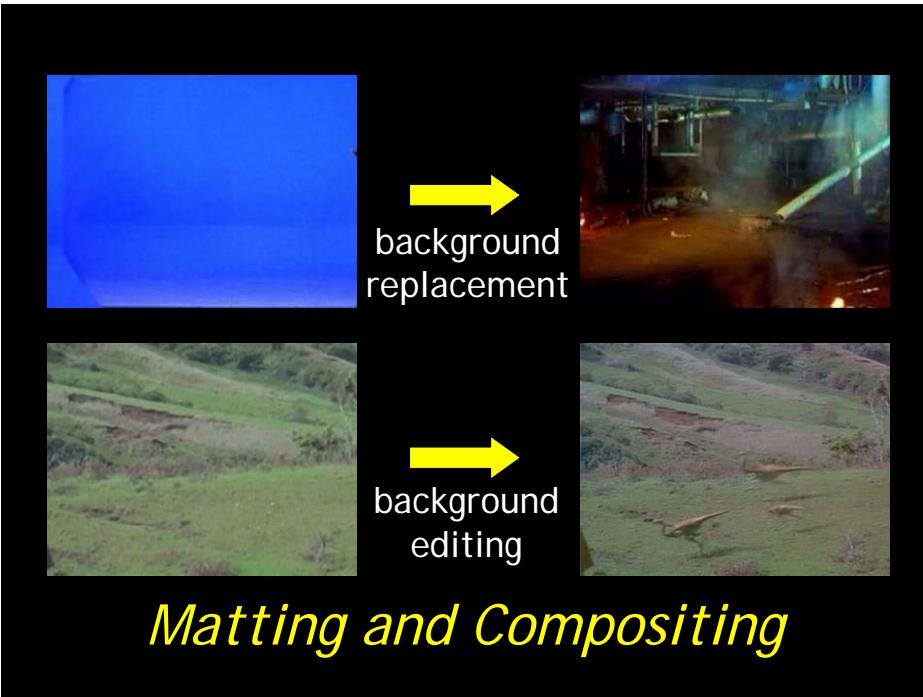


Oscar award, 1996

Titanic



Matting and Compositing

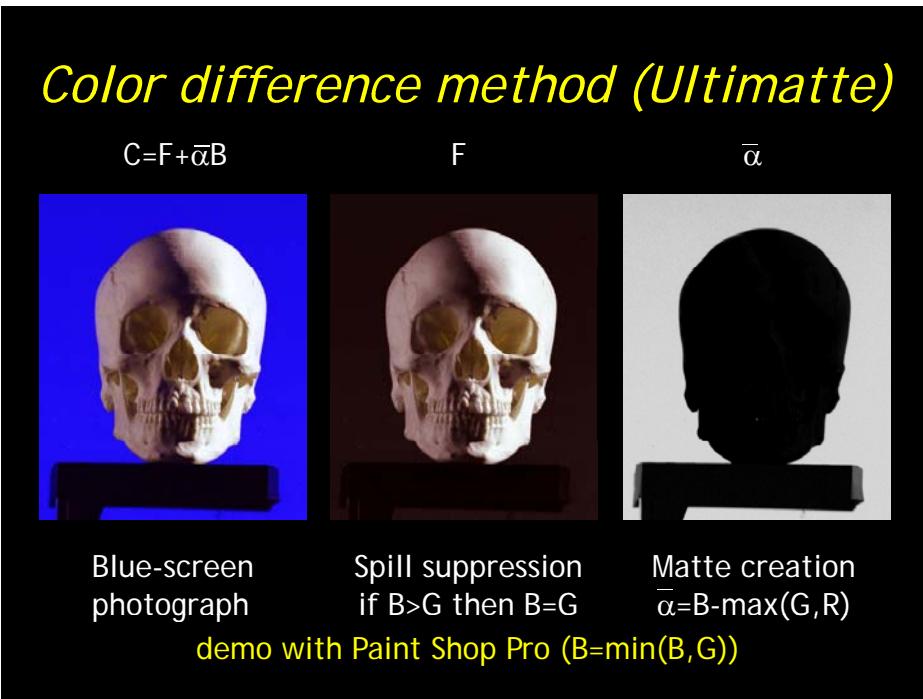


Digital matting: bluescreen matting



Forrest Gump (1994)

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

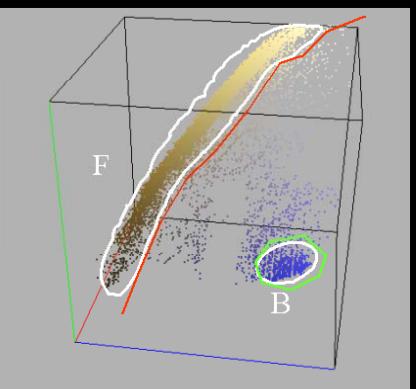


Problems with color difference

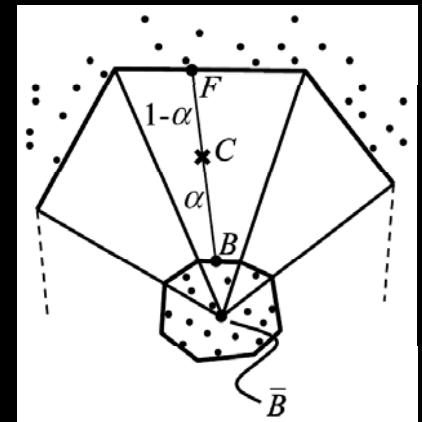
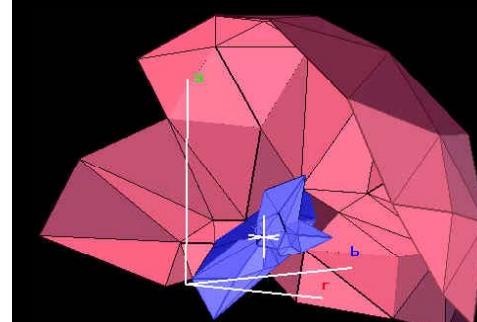


Background color is usually not perfect! (lighting, shadowing...)

Chroma-keying (Primate)



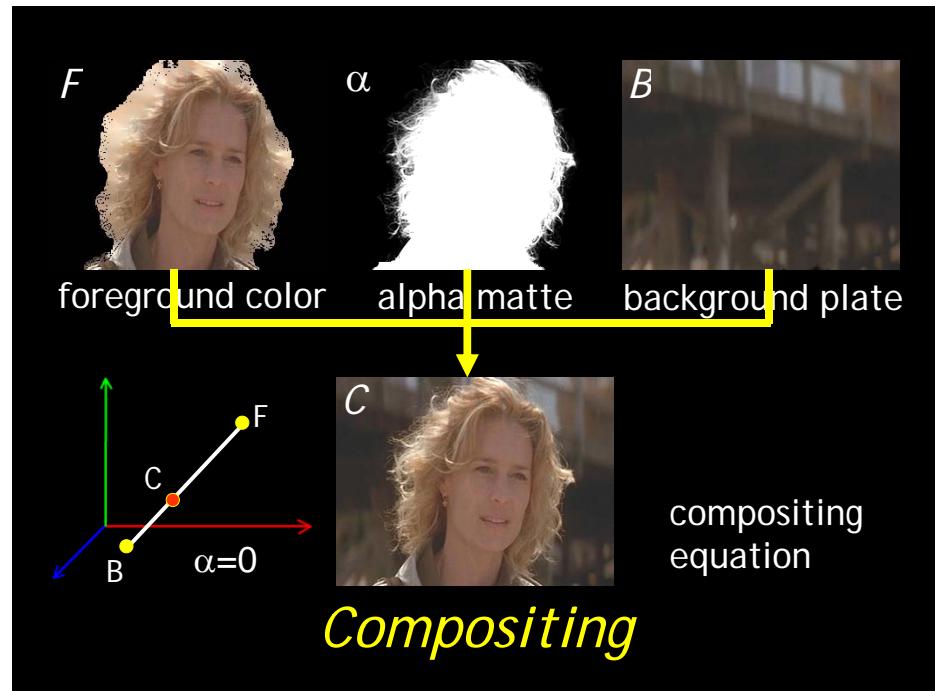
Chroma-keying (Primate)

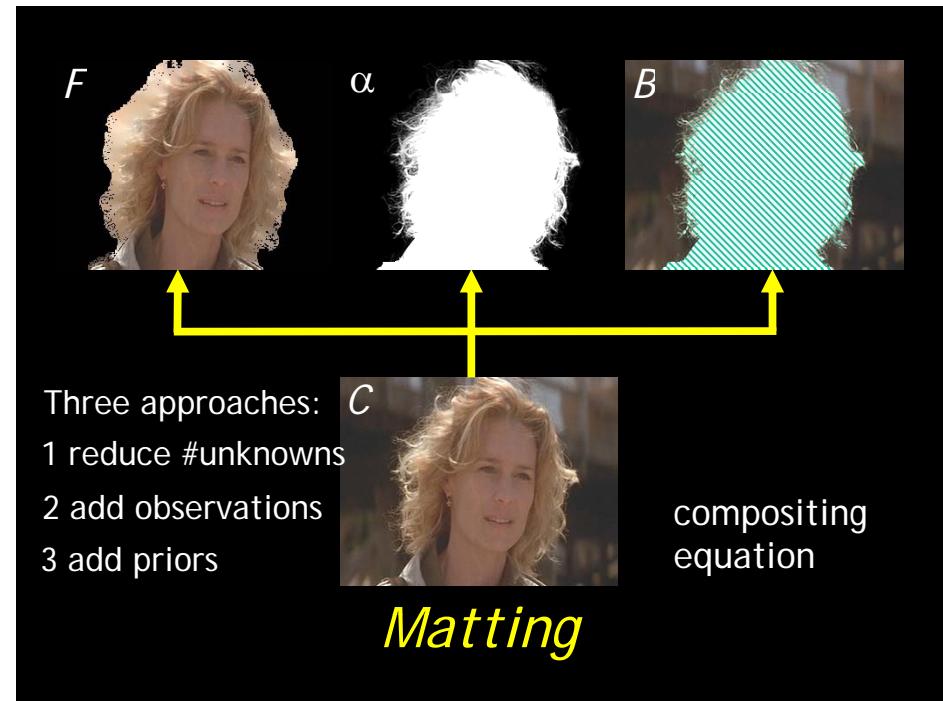
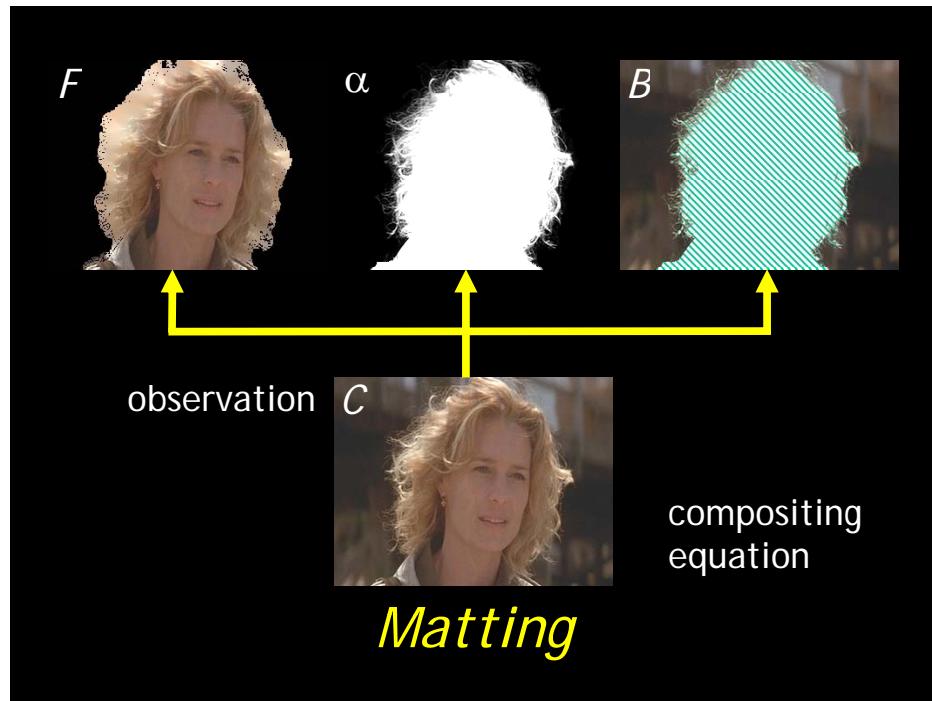
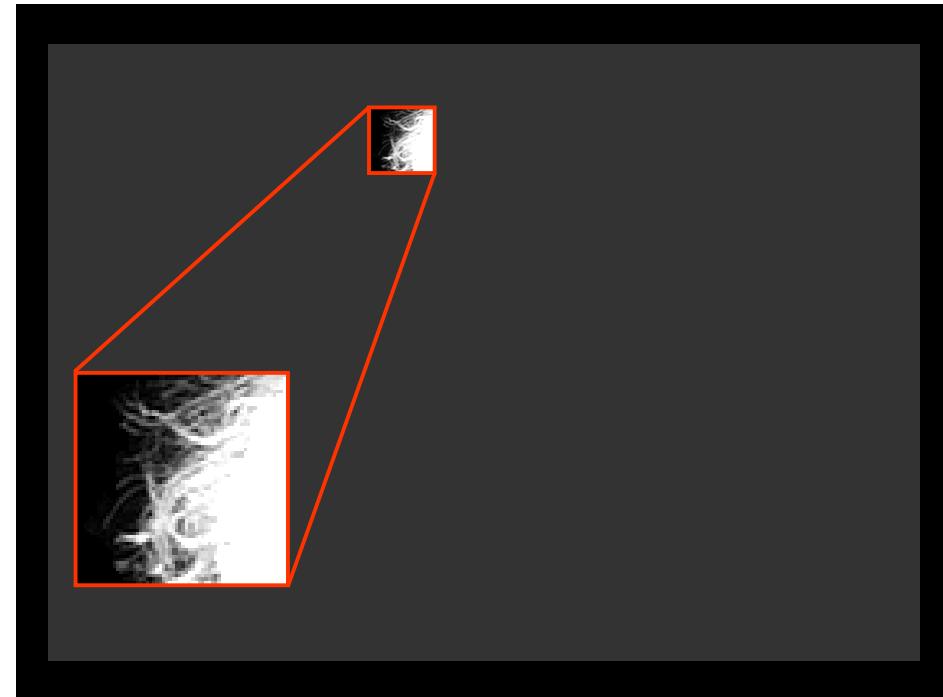
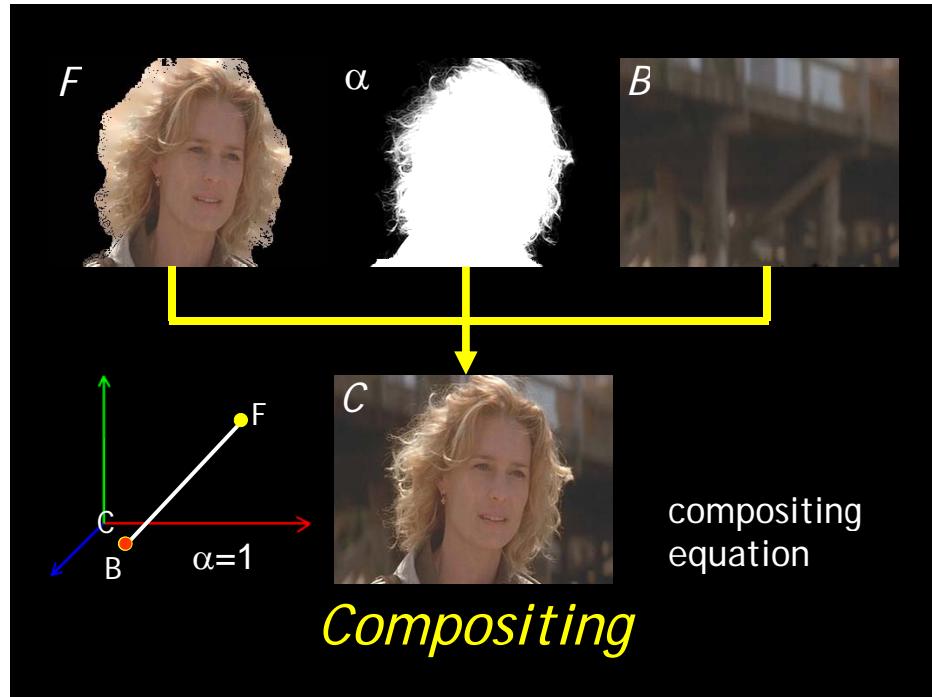


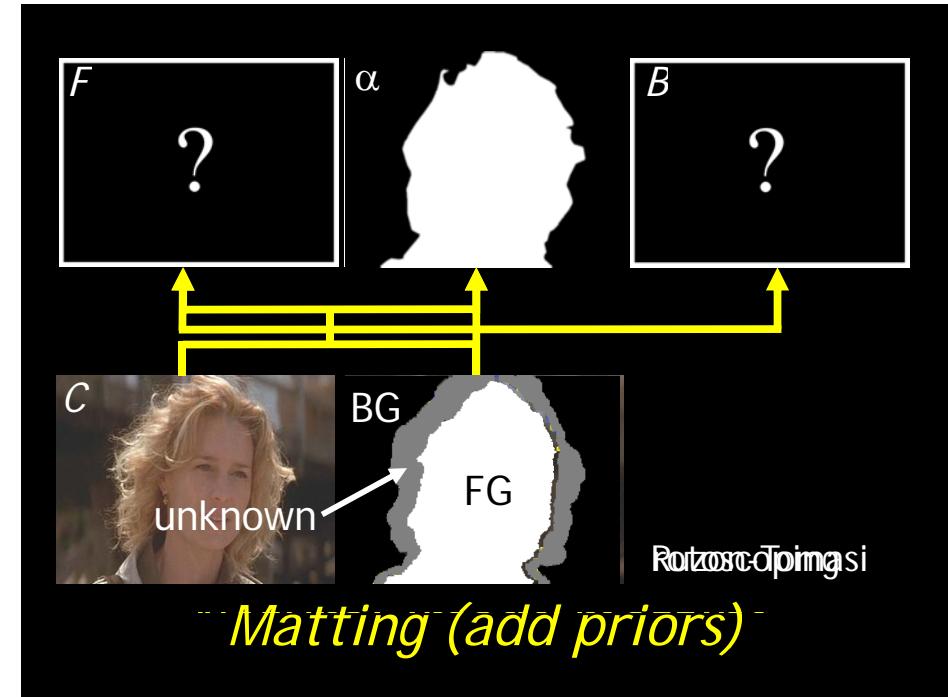
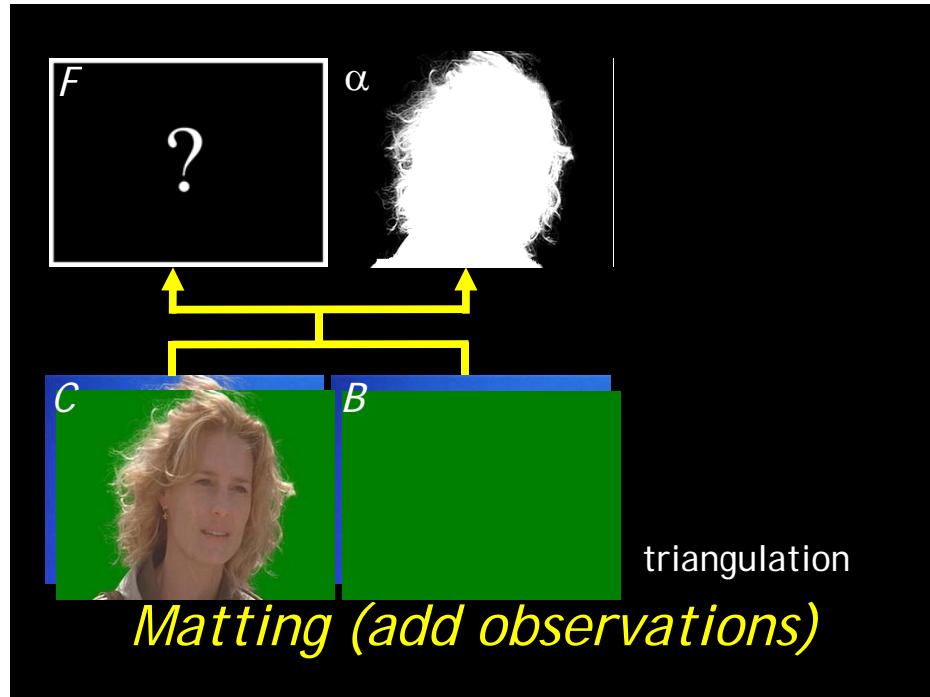
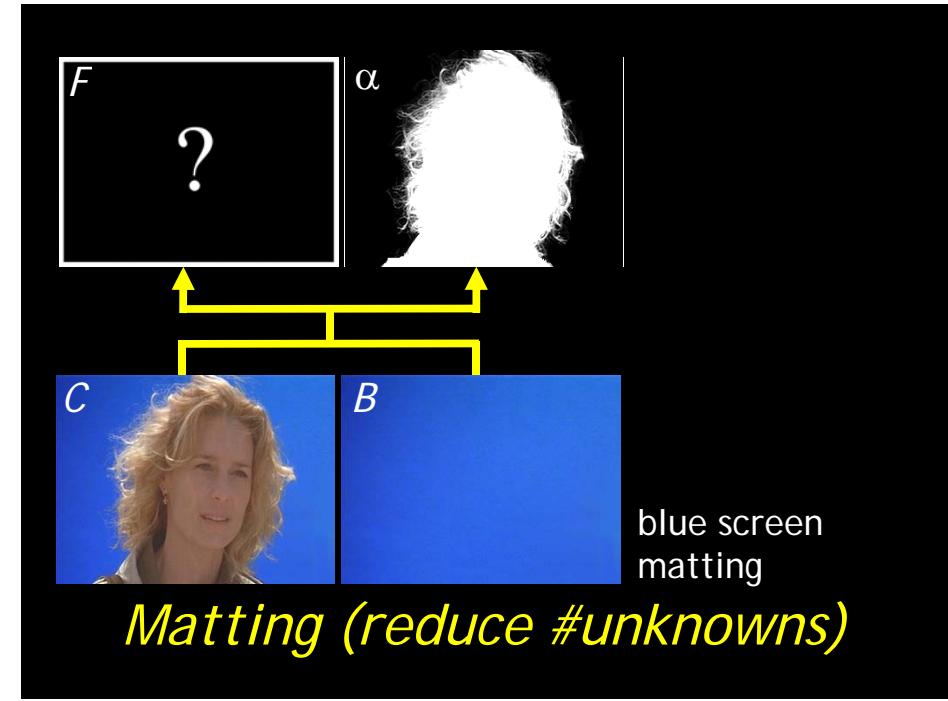
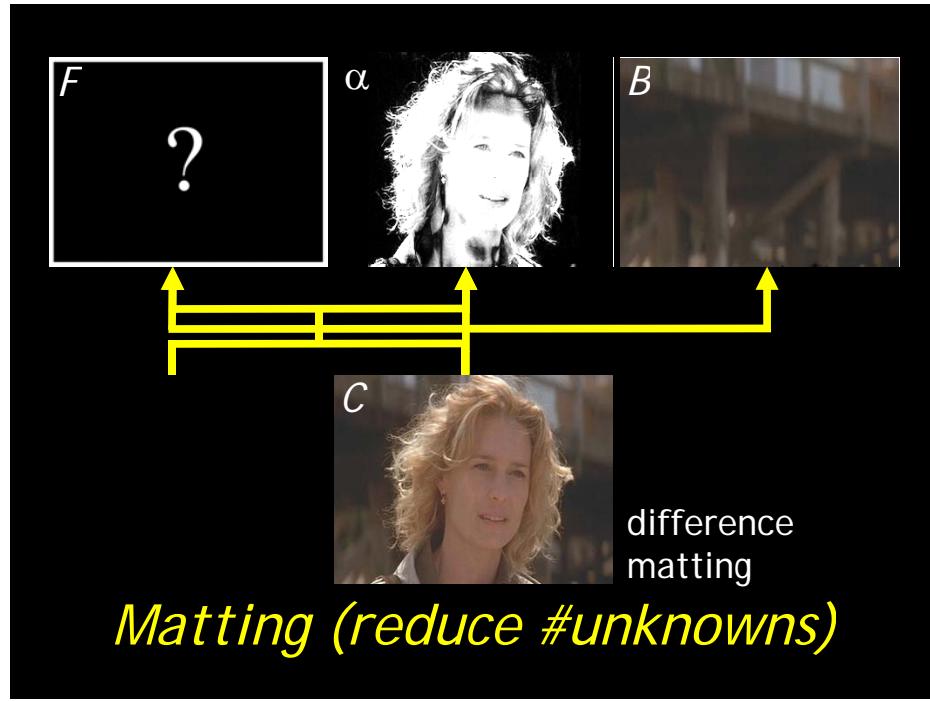
[demo](#)

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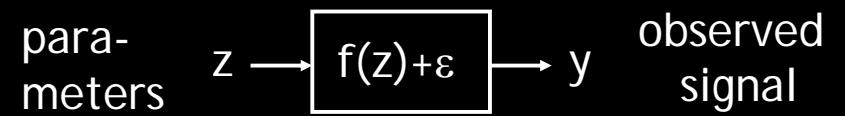






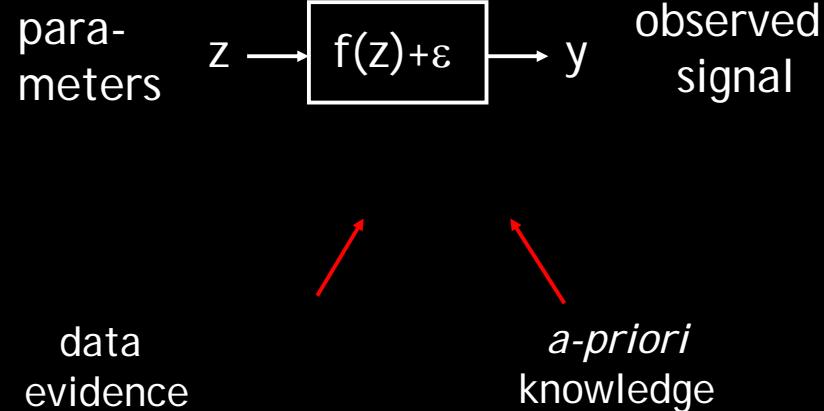
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Example:
super-resolution
de-blurring
de-blocking
...

Bayesian framework



Bayesian framework

posterior probability

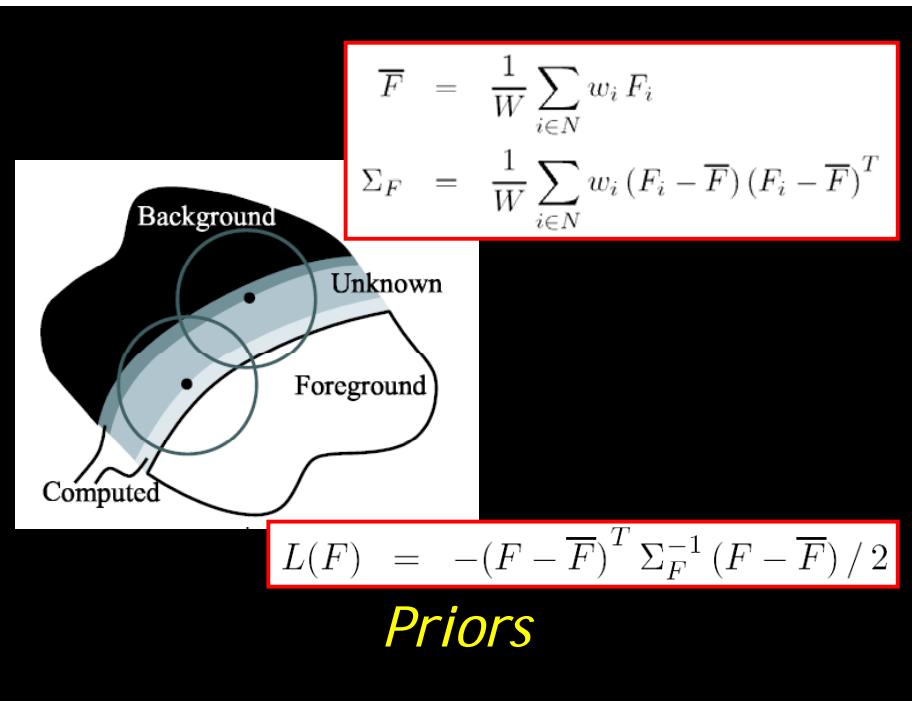
$$\arg \max_{F,B,\alpha} P(F, B, \alpha | C)$$
$$= \arg \max_{F,B,\alpha} P(C | F, B, \alpha) P(F) P(B) P(\alpha) / P(C)$$

likelihood priors

```
graph TD; PP[posterior probability] --> PostP[P(C | F, B, alpha)]; PostP -- likelihood --> L[P(F) P(B) P(alpha) / P(C)]; PostP -- priors --> P[P(F) P(B) P(alpha) / P(C)]; PostP -- posterior probability --> PostP
```

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

Bayesian framework



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

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

$$-(F - \bar{F})^T \Sigma_F^{-1} (F - \bar{F}) / 2$$

$$-(B - \bar{B})^T \Sigma_B^{-1} (B - \bar{B}) / 2$$

Bayesian matting

repeat

1. fix alpha

$$\begin{bmatrix} \Sigma_F^{-1} + I\alpha^2/\sigma_C^2 & I\alpha(1-\alpha)/\sigma_C^2 \\ I\alpha(1-\alpha)/\sigma_C^2 & \Sigma_B^{-1} + I(1-\alpha)^2/\sigma_C^2 \end{bmatrix} \begin{bmatrix} F \\ B \end{bmatrix}$$

$$= \begin{bmatrix} \Sigma_F^{-1}\bar{F} + C\alpha/\sigma_C^2 \\ \Sigma_B^{-1}\bar{B} + C(1-\alpha)/\sigma_C^2 \end{bmatrix}$$

2. fix F and B

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

until converge

Optimization





Bayesian image matting



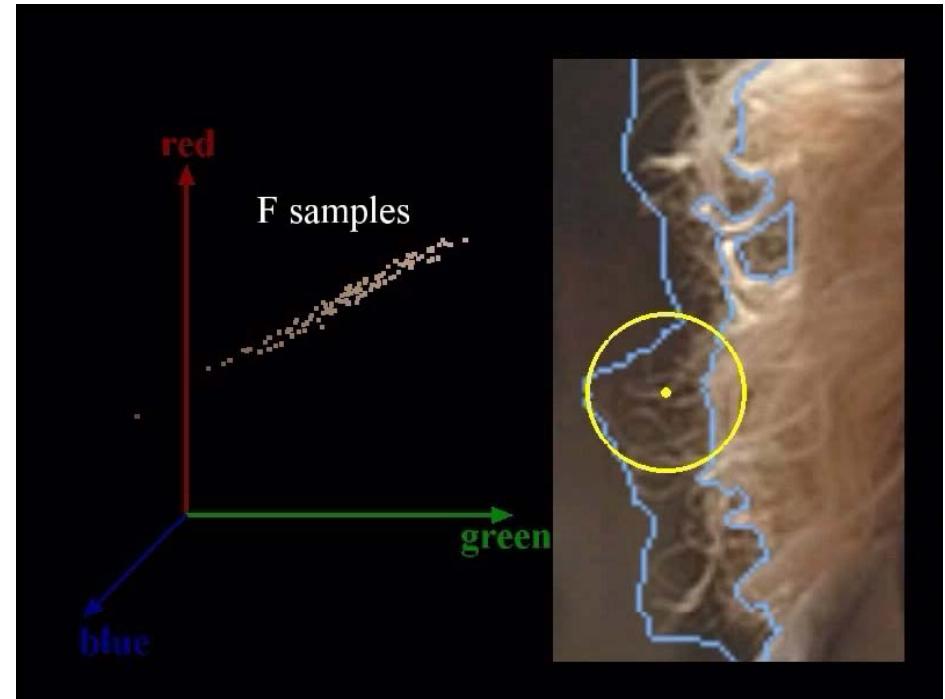
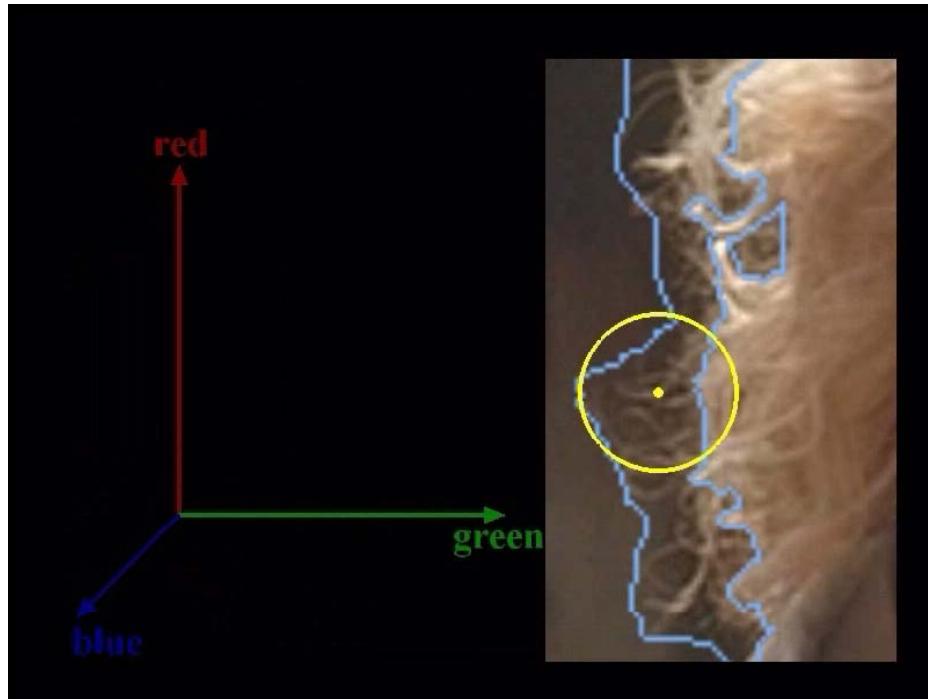
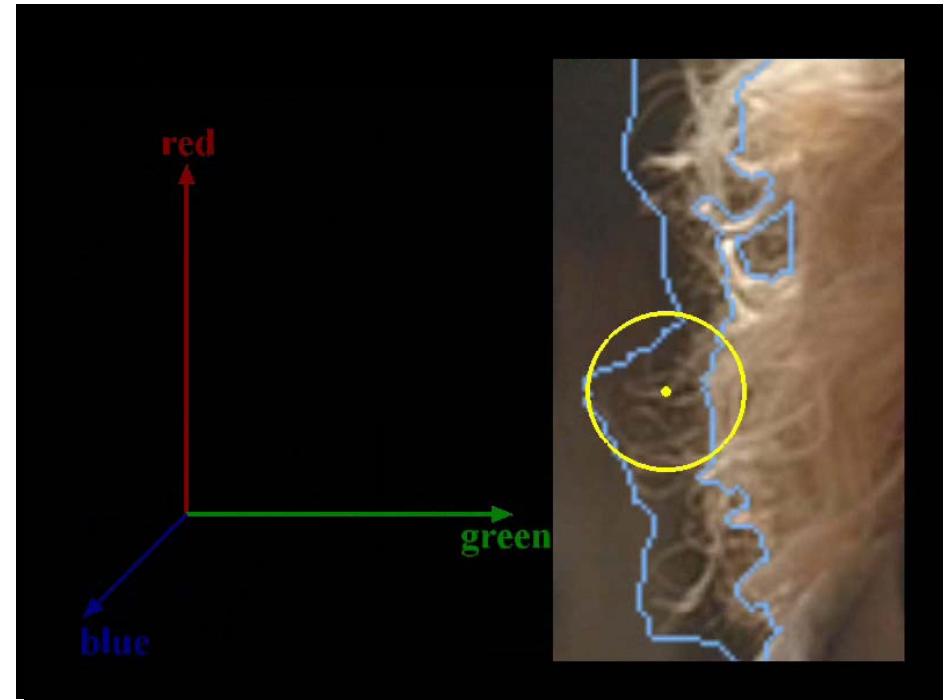
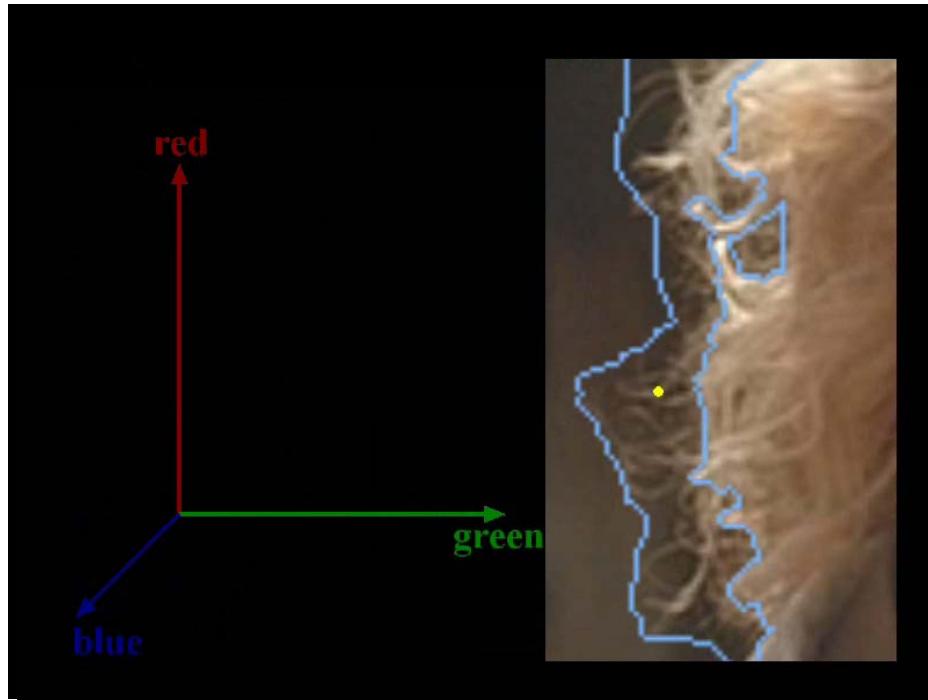
Bayesian image matting

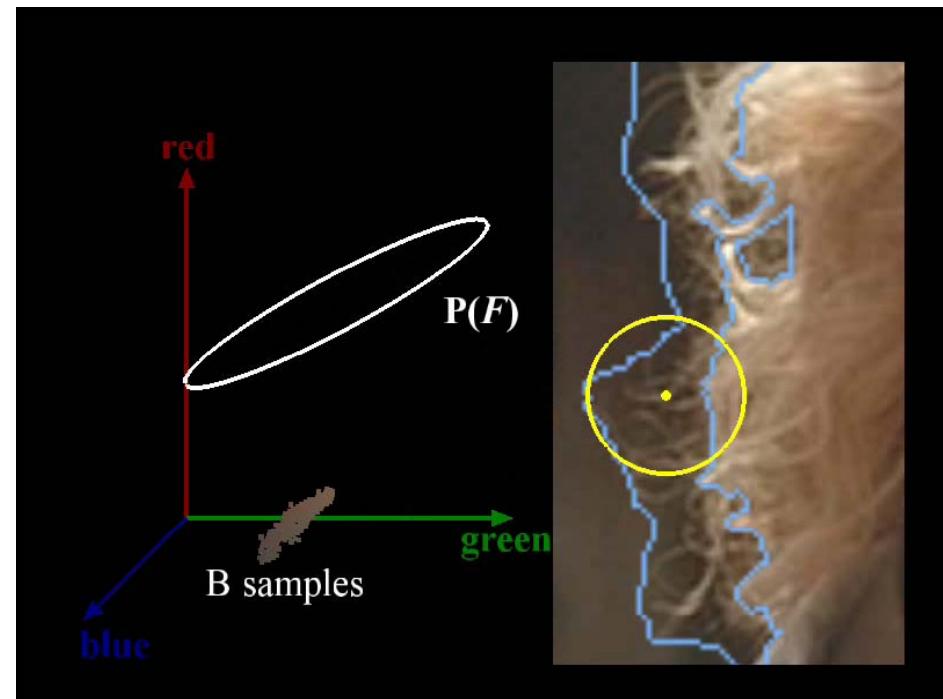
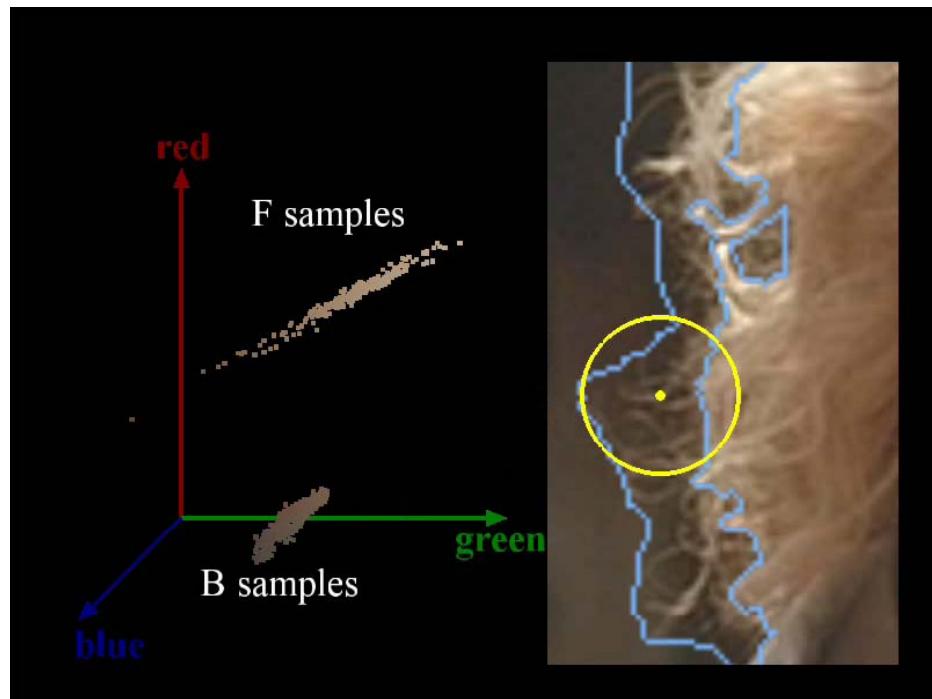
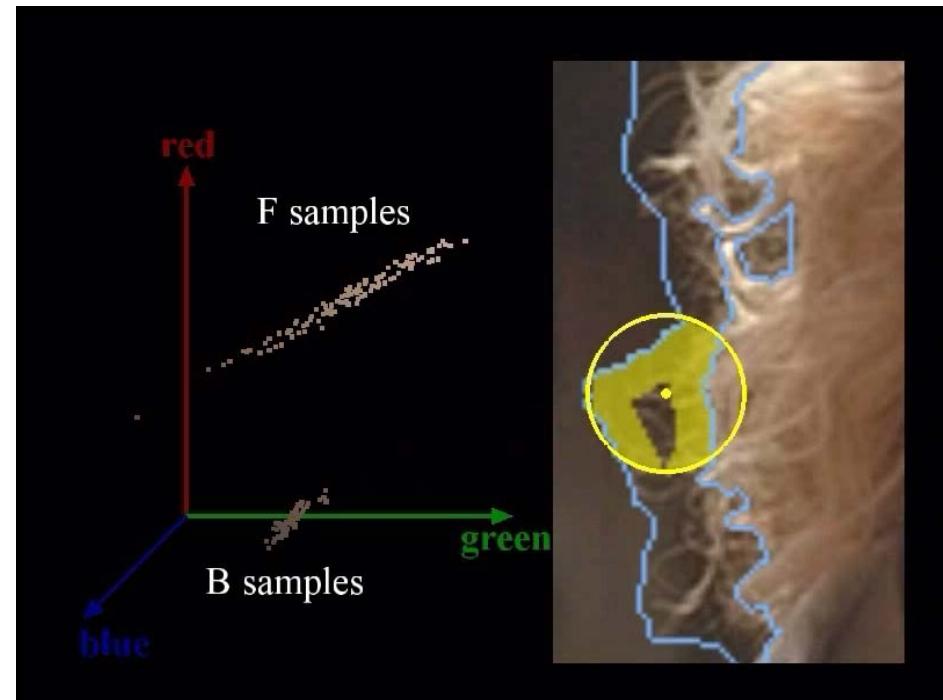
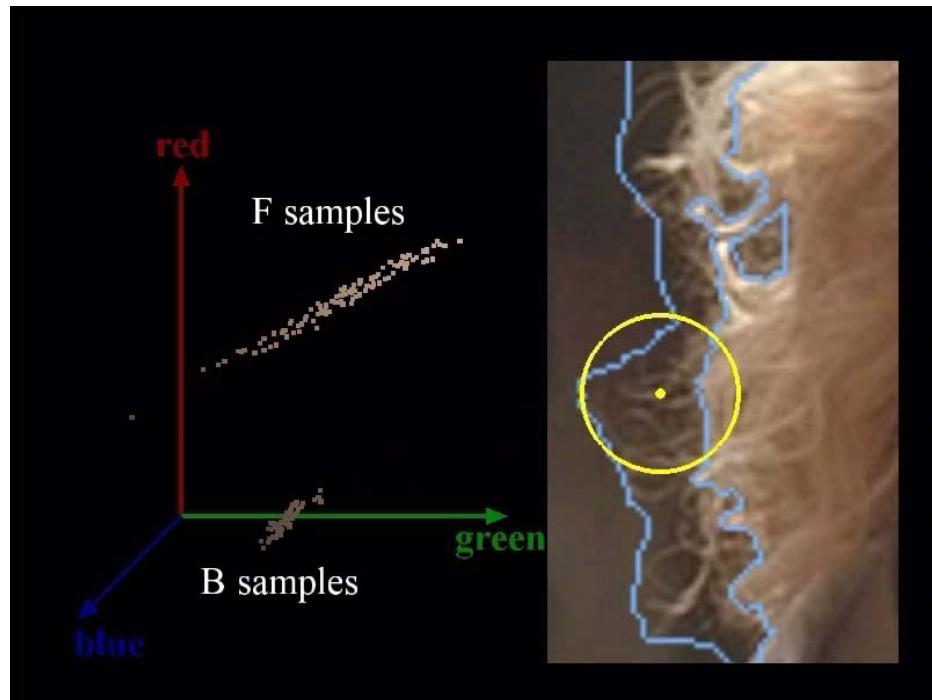


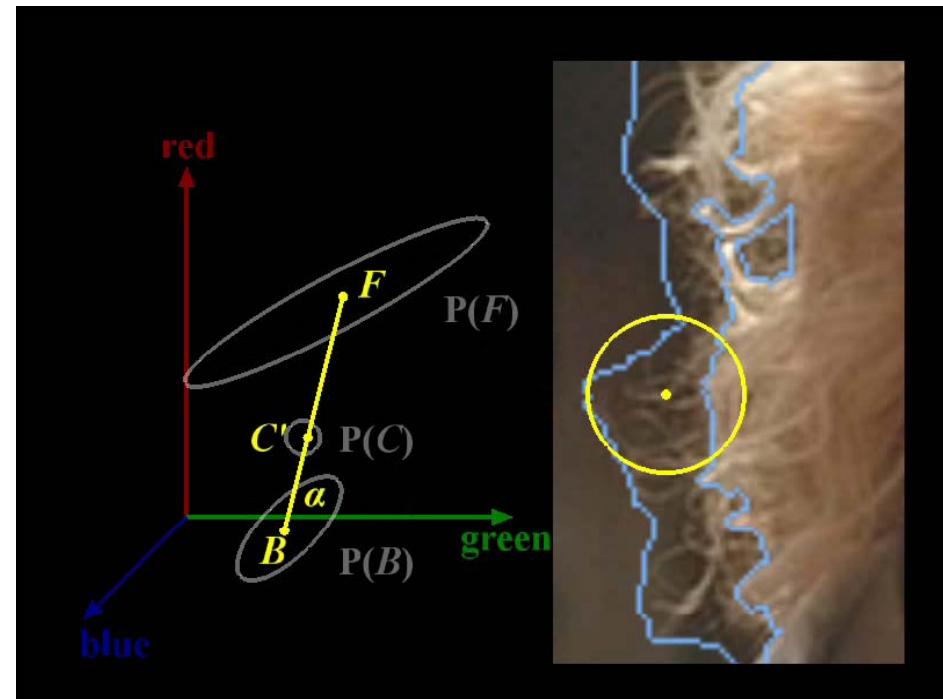
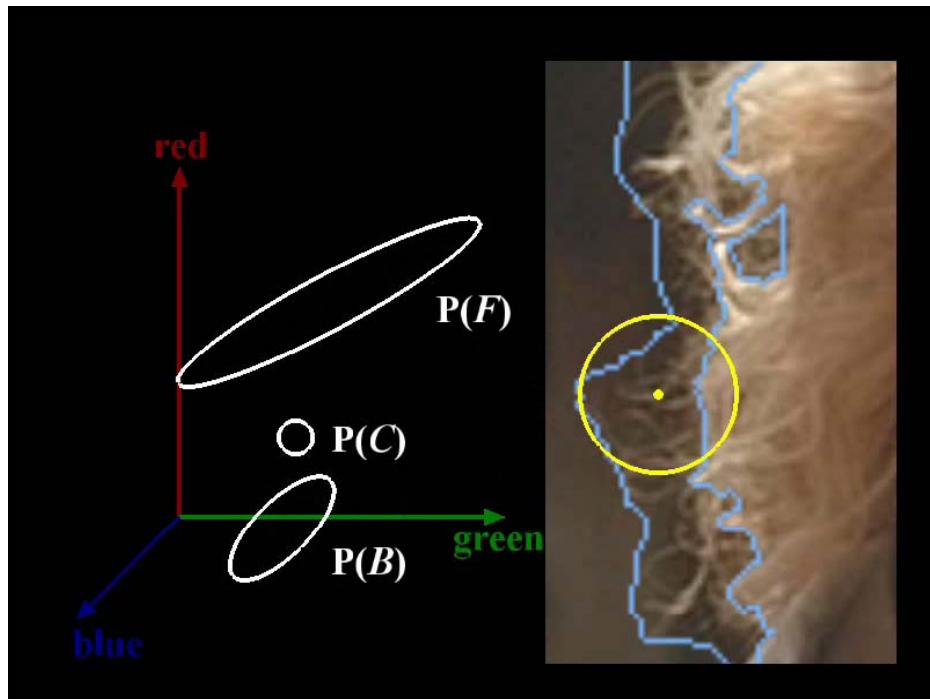
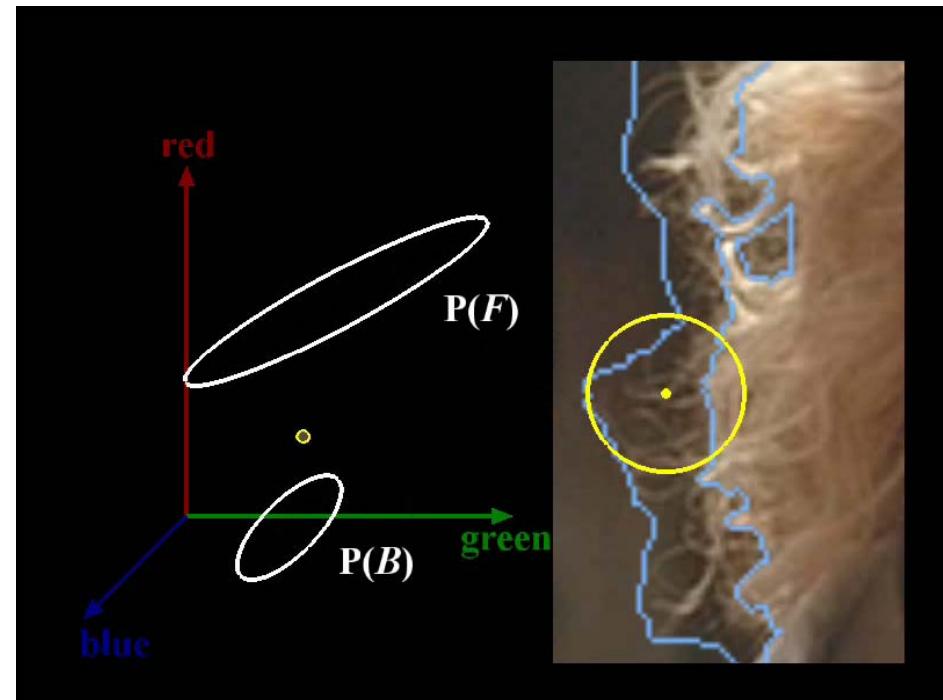
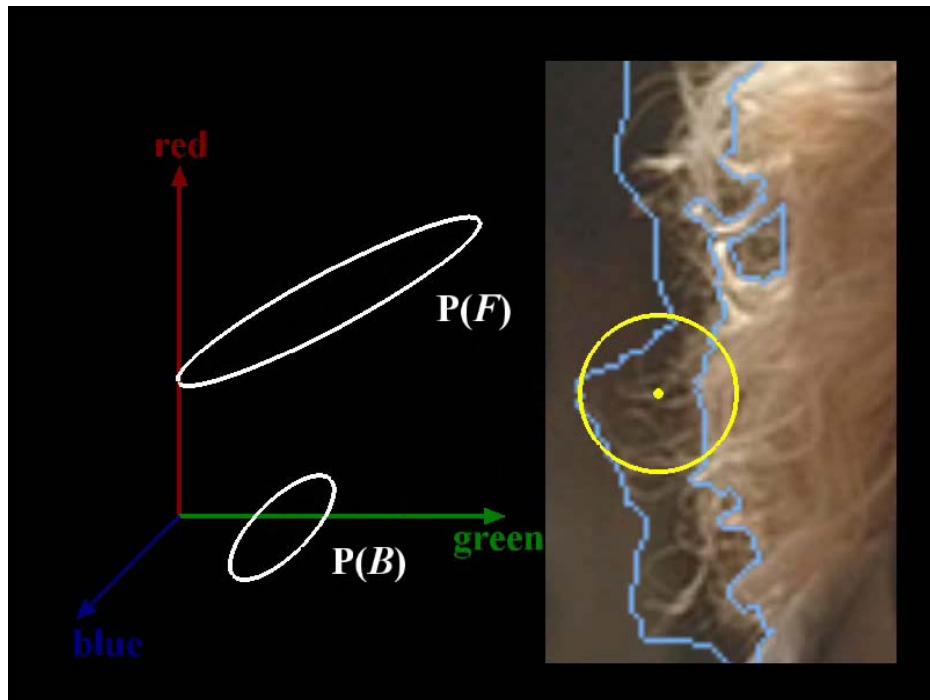
Bayesian image matting



Bayesian image matting









Demo

alpha



Results

input



composite



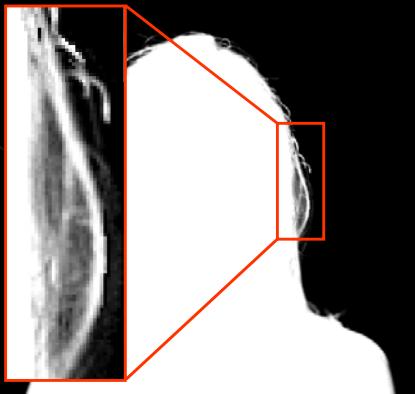
Results

trimap

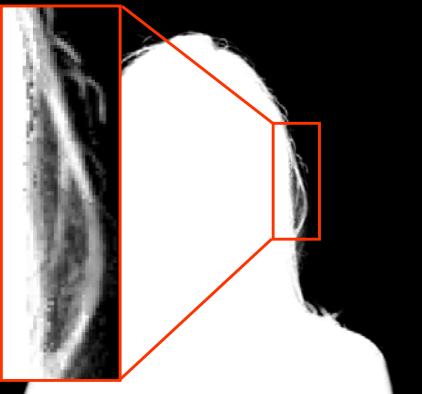


Comparisons

Bayesian

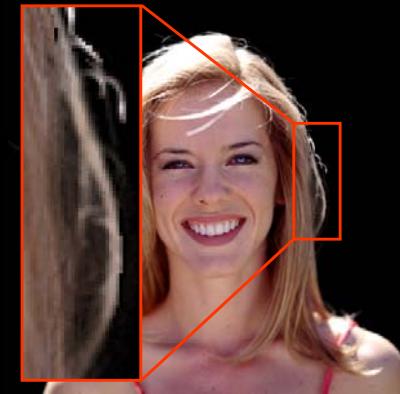


Ruzon-Tomasi

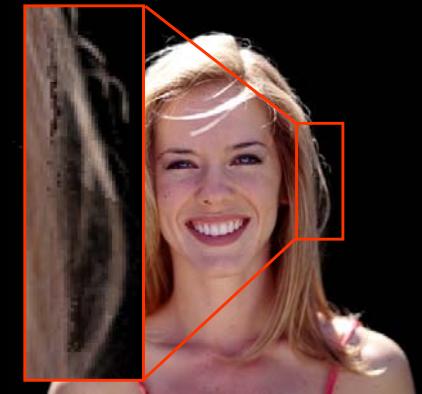


Comparisons

Bayesian



Ruzon-Tomasi



Comparisons

Mishima



Comparisons

Bayesian



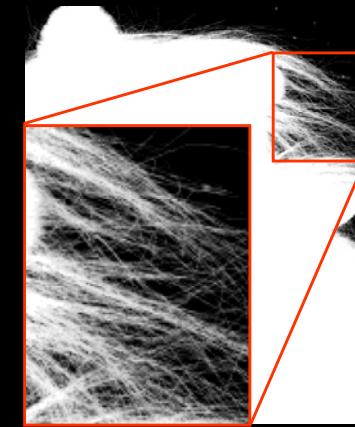
Comparisons

input image



Comparisons

Bayesian



Mishima



Comparisons

Bayesian



Mishima



Comparisons

input
video



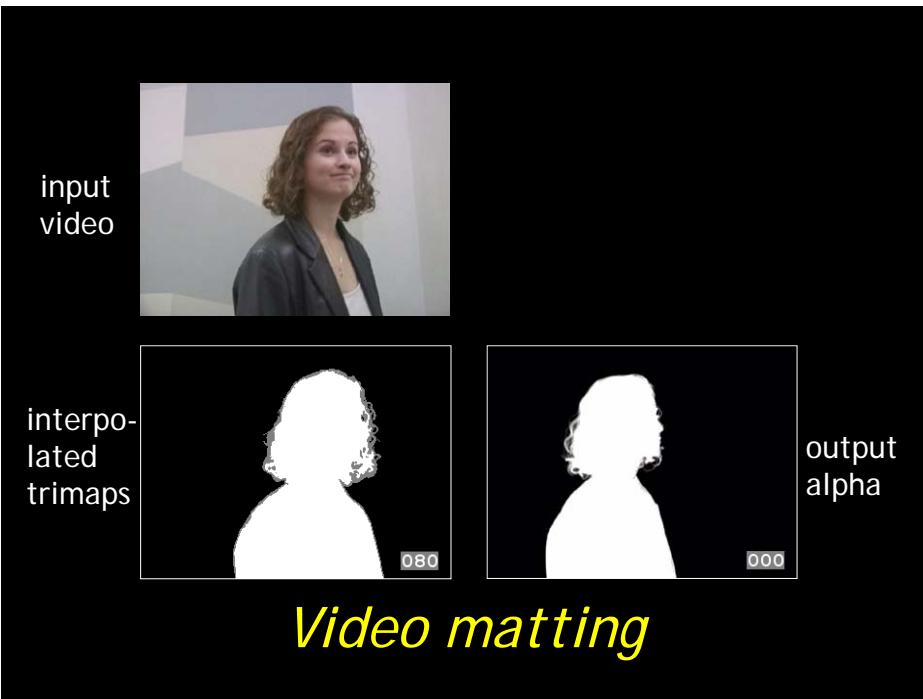
Video matting



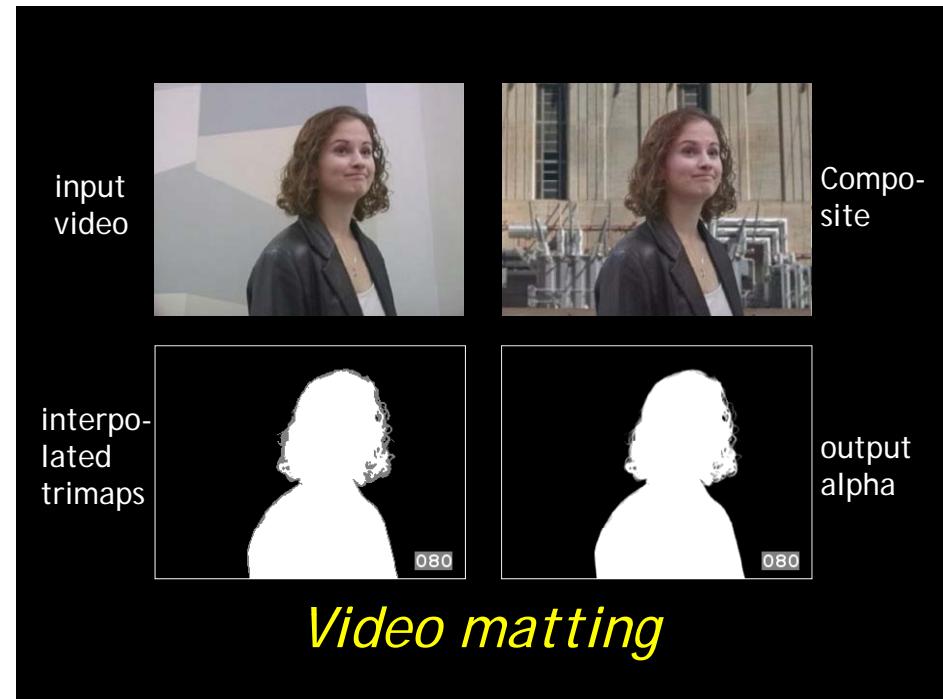
Video matting



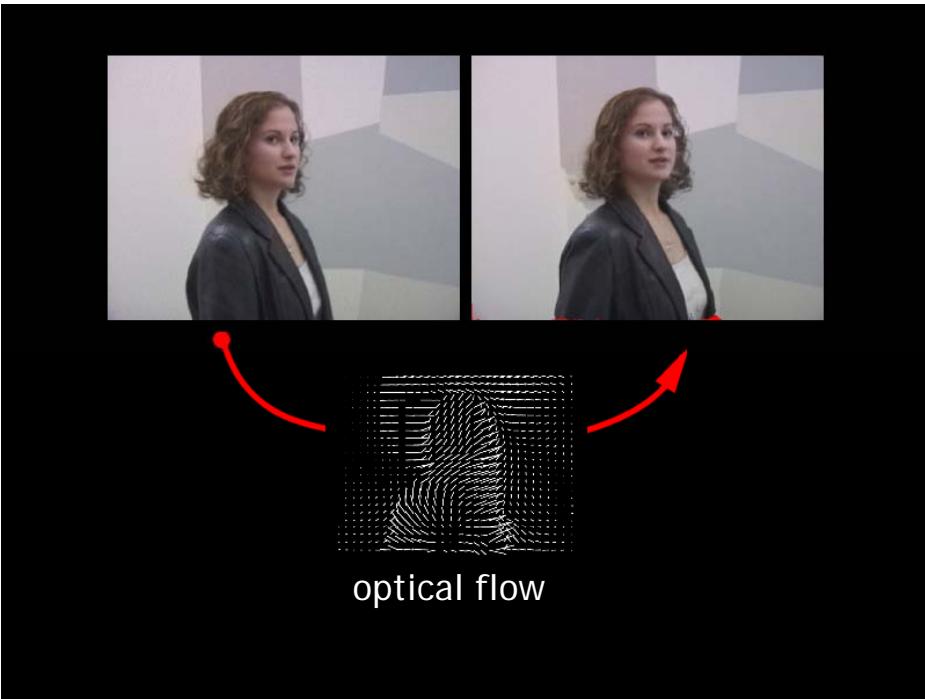
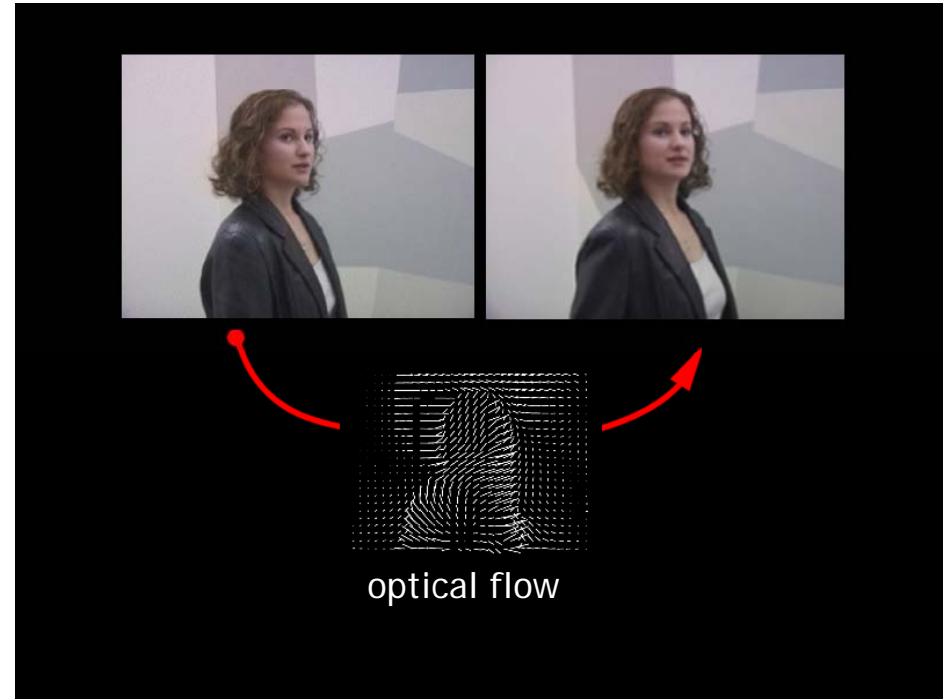
Video matting

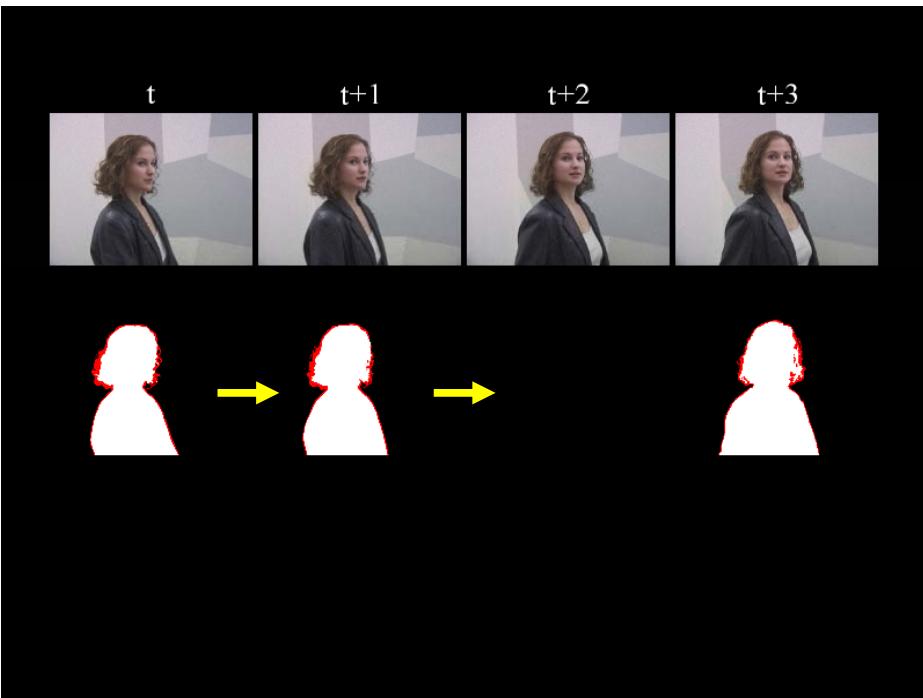


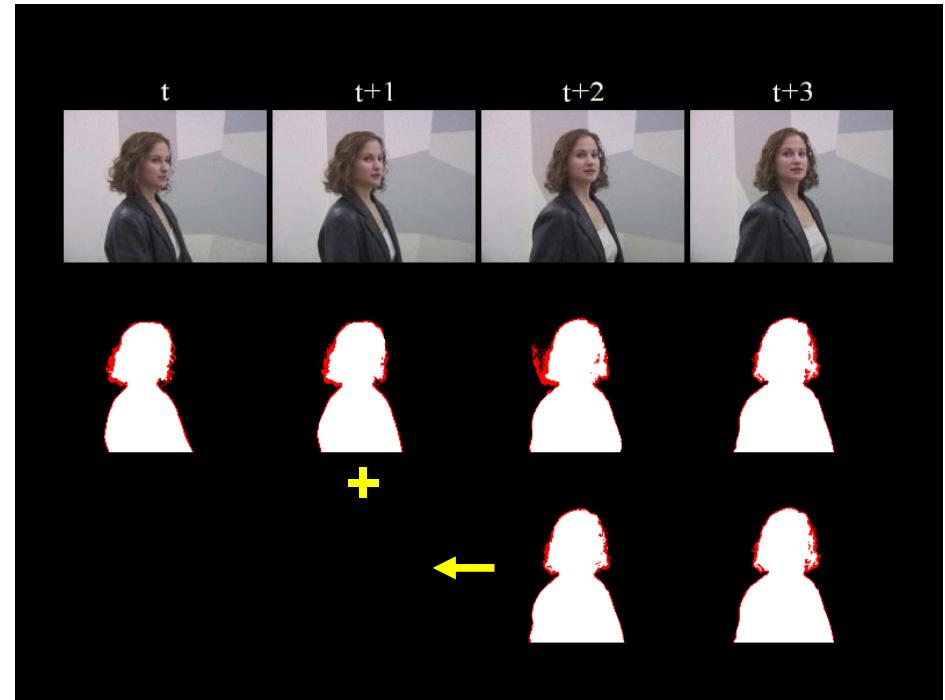
Video matting



Video matting





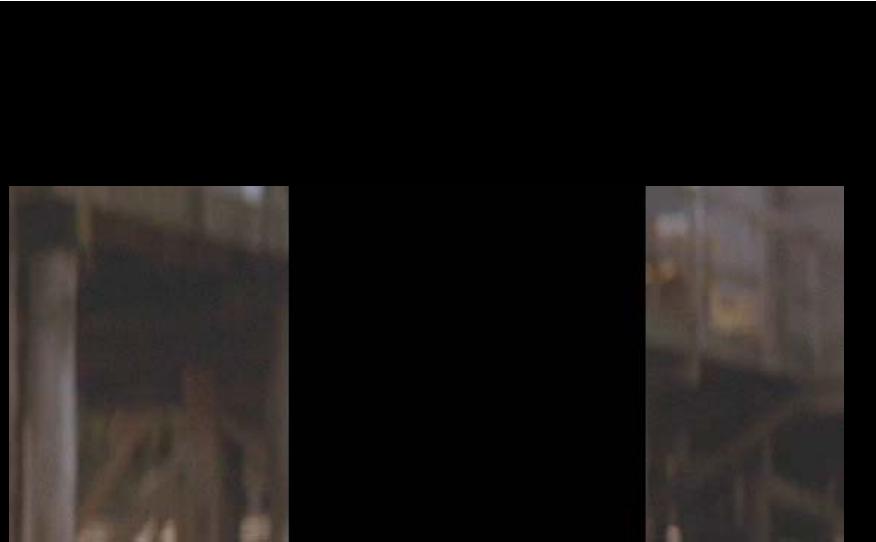




Garbage mattes



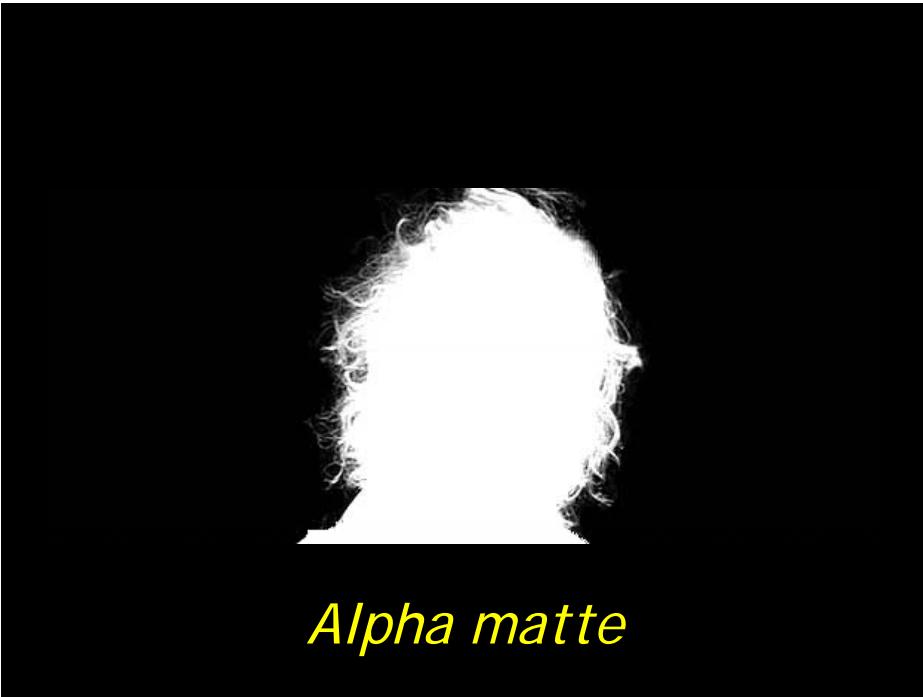
Garbage mattes



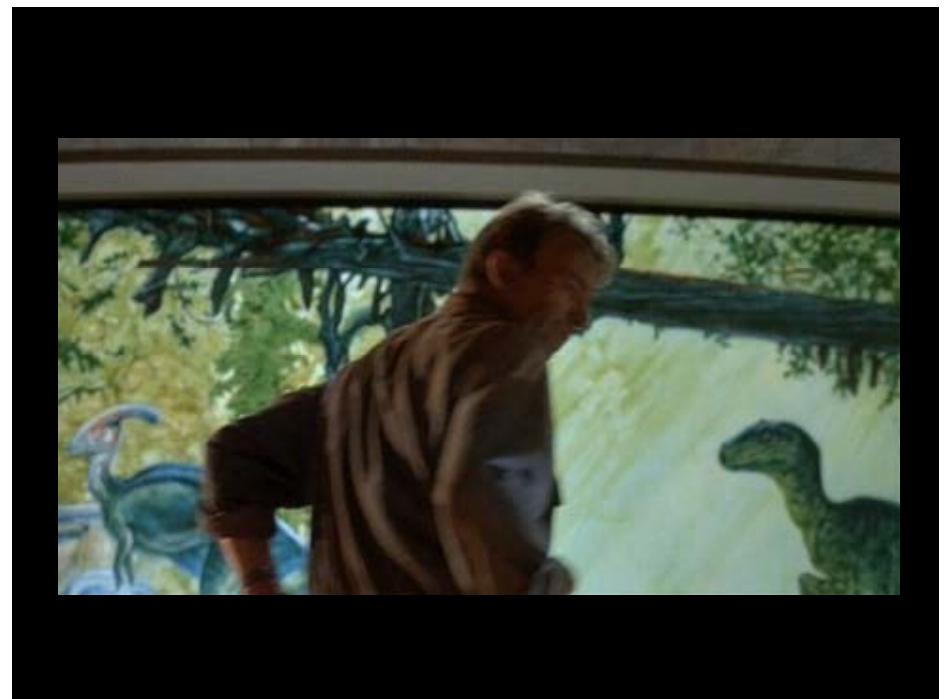
Background estimation

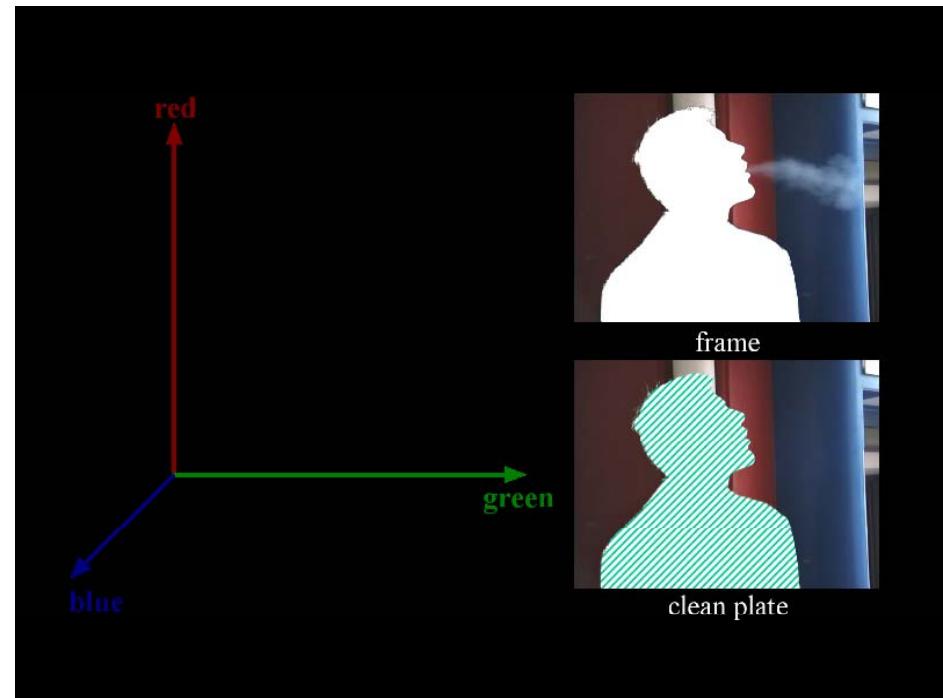
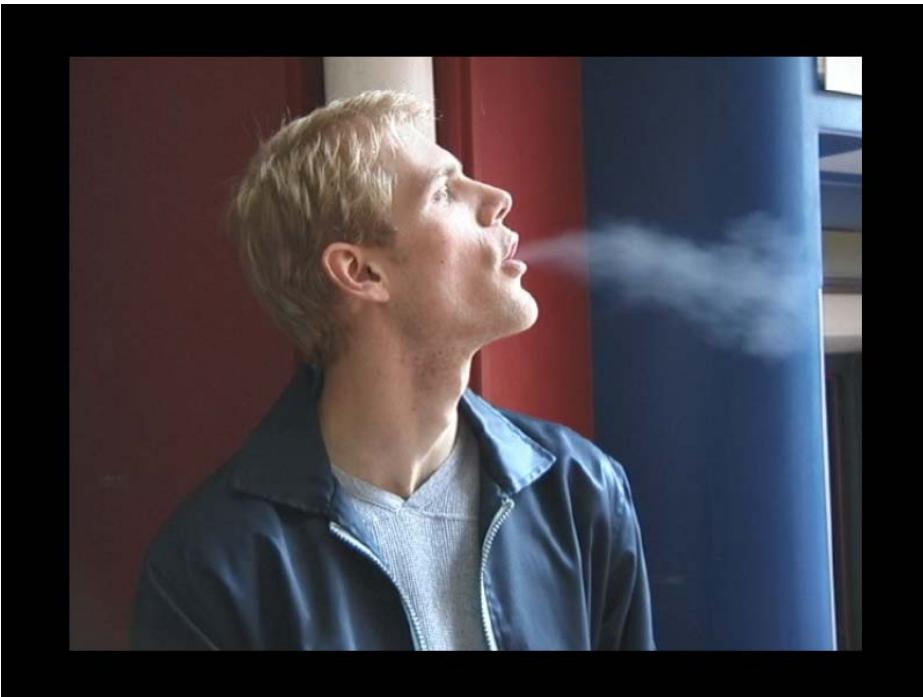


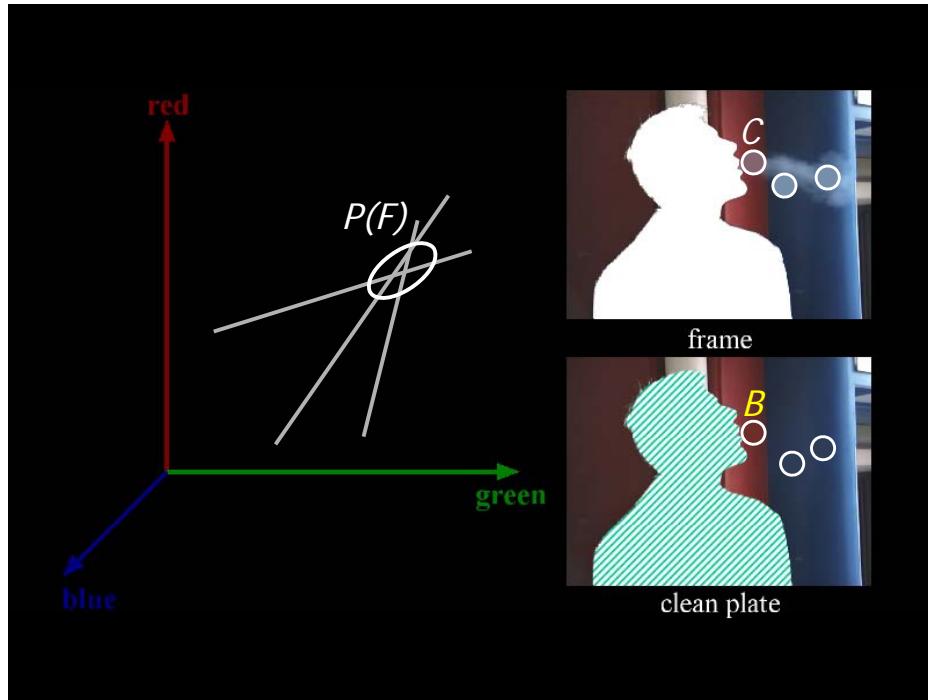
Background estimation



Alpha matte







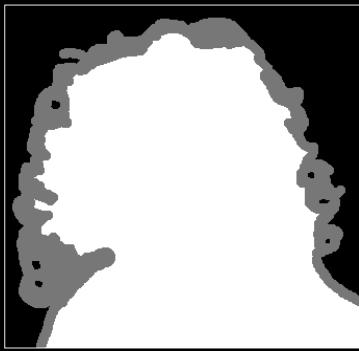
Problems with Bayesian matting

- 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 resulting mattes

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Scribble-based input



trimap

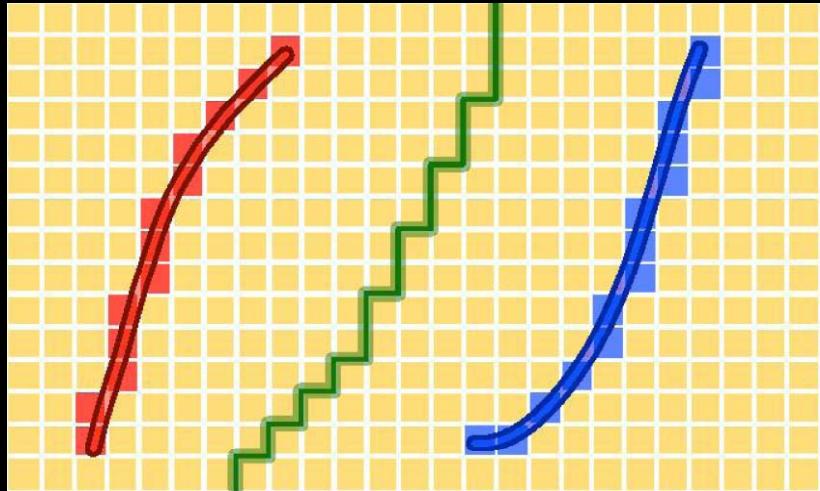


scribble

Motivation



LazySnapping



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

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

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

$$E_1(x_i = 1) = \frac{d_i^{\mathcal{F}}}{d_i^{\mathcal{F}} + d_i^{\mathcal{B}}} \quad E_1(x_i = 0) = \frac{d_i^{\mathcal{B}}}{d_i^{\mathcal{F}} + d_i^{\mathcal{B}}} \quad \forall i \in \mathcal{U}$$

$$d_i^{\mathcal{F}} = \min_n \|C(i) - K_n^{\mathcal{F}}\|$$

n-th mean foreground color

LazySnapping

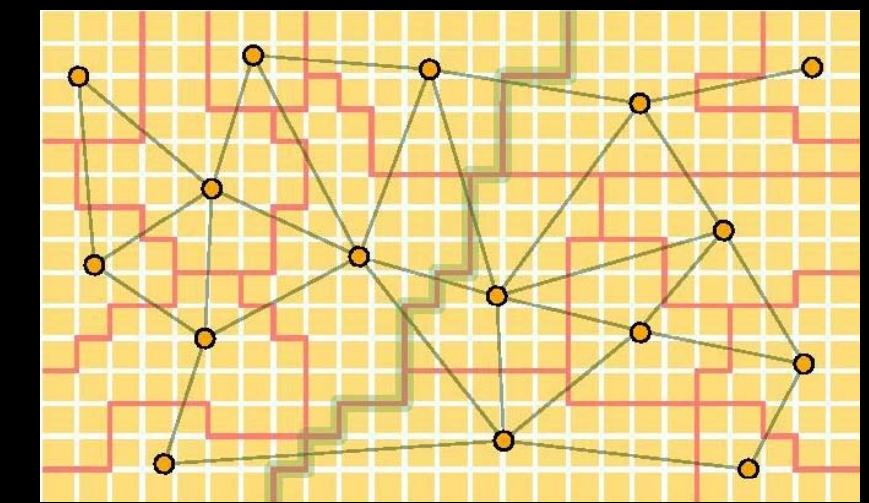
$$E(X) = \sum_{i \in \mathcal{V}} E_1(x_i) + \lambda \sum_{(i,j) \in \mathcal{E}} E_2(x_i, x_j)$$

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

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

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

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

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

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

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

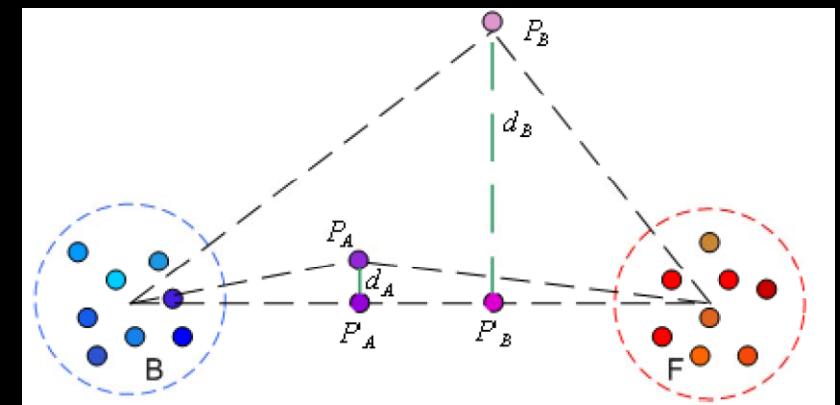
$$\alpha^* = \arg \min_{\alpha} \int \int_{p \in \Omega} \|\nabla\alpha_p - \frac{1}{F_p - B_p} \nabla I_p\|^2 dp$$

Poisson matting



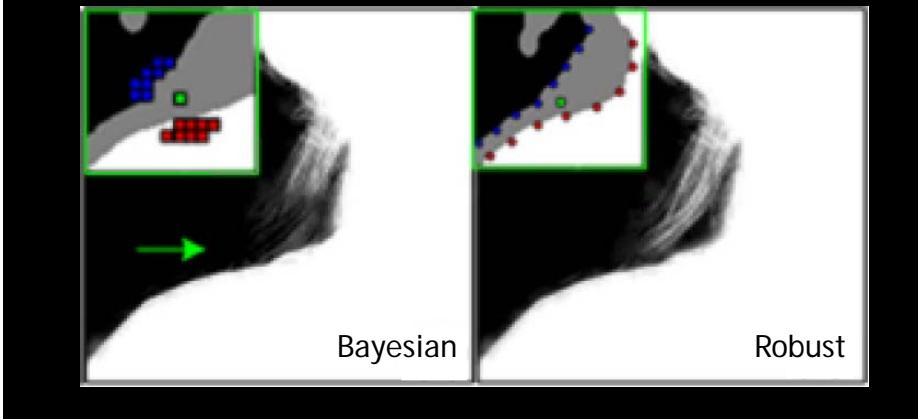
Robust matting

- Jue Wang and Michael Cohen, CVPR 2007



Robust matting

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



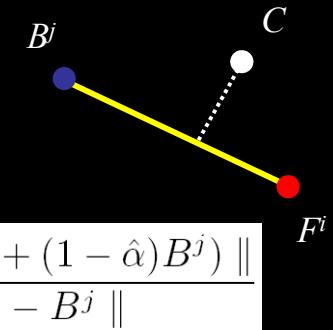
Robust matting

- We must evaluate hypothesized foreground/background pairs

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

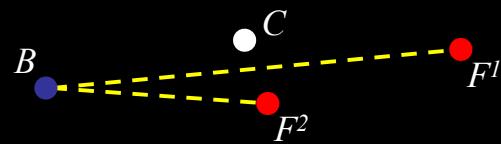
distance ratio

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



Robust matting

- To encourage pure fg/bg pixels, add weights



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

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

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

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

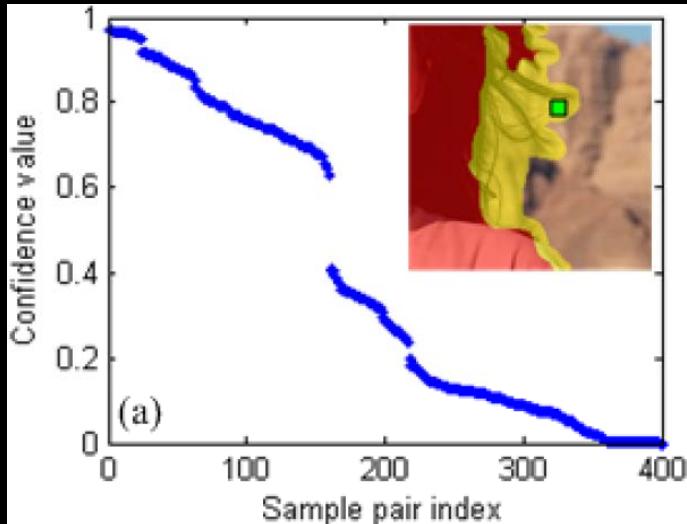
Robust matting

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

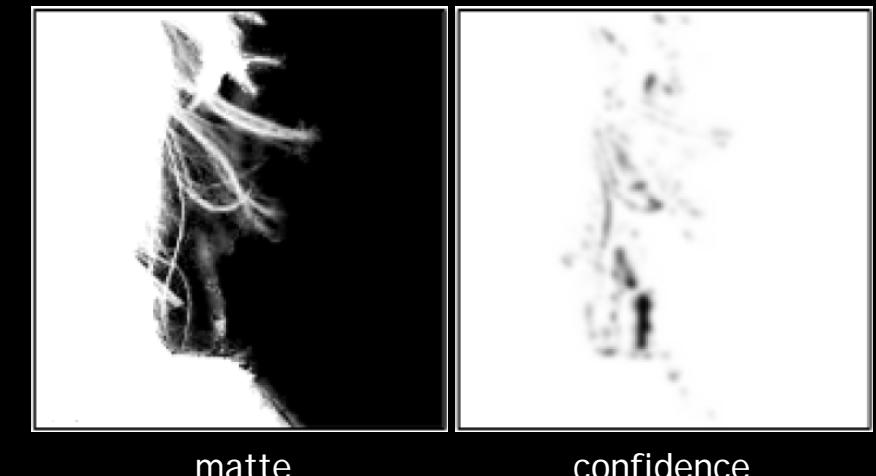
confidence

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

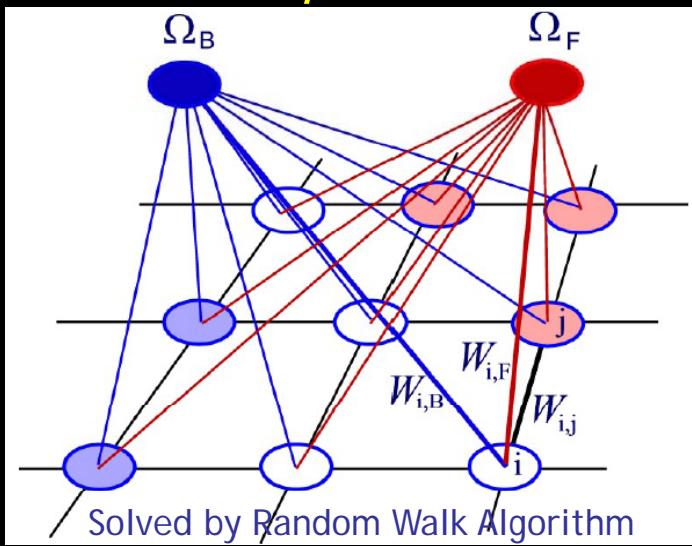
Robust matting



Robust matting



Matte 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

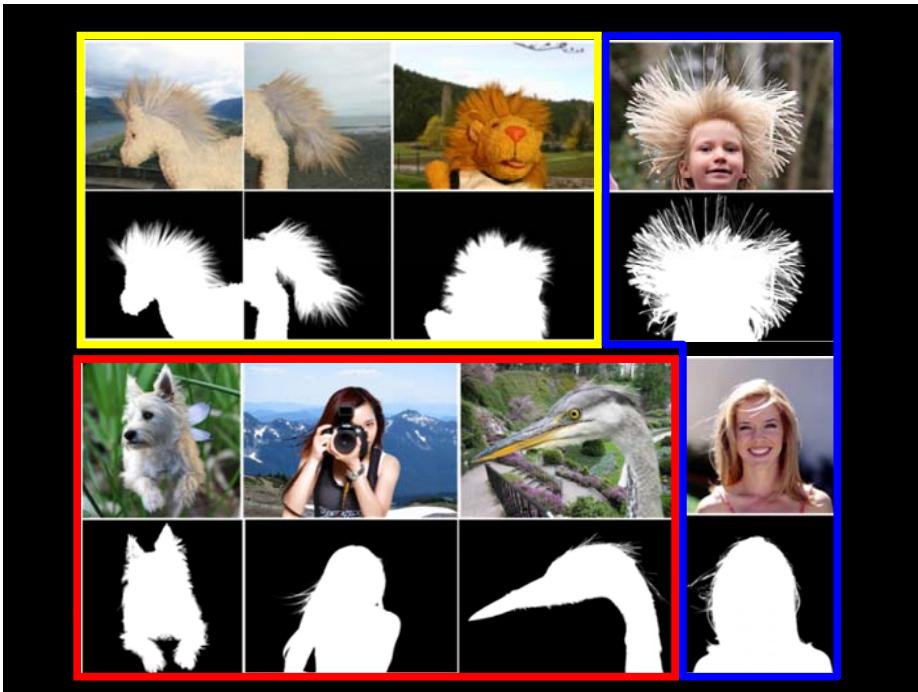
$$W_{ij} = \sum_k^{(i,j) \in w_k} \frac{1}{9} (1 + (C_i - \mu_k)(\Sigma_k + \frac{\epsilon}{9} I)^{-1}(C_j - \mu_k))$$

Demo (EZ Mask)



Evaluation

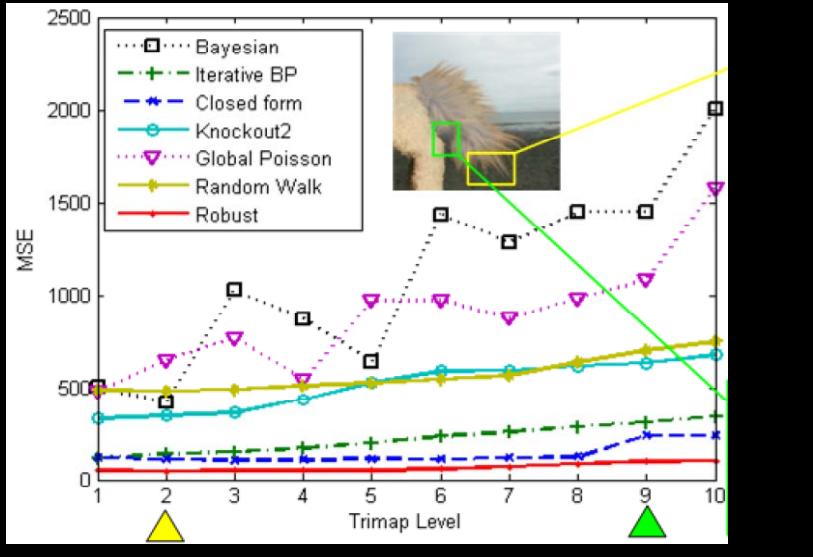
- 8 images collected in 3 different ways
- Each has a “ground truth” matte



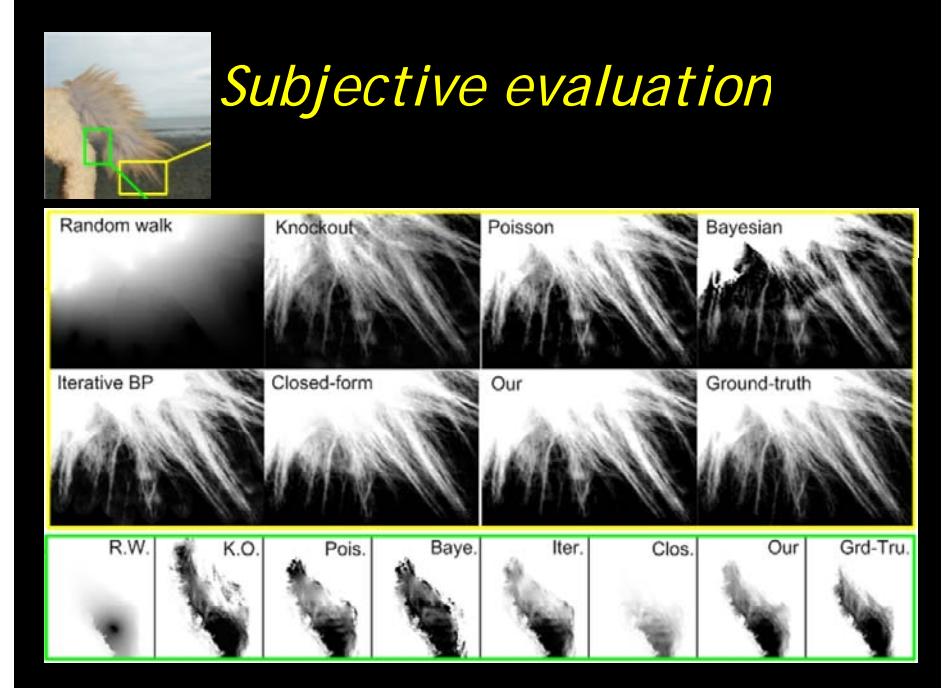
Evaluation

- 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

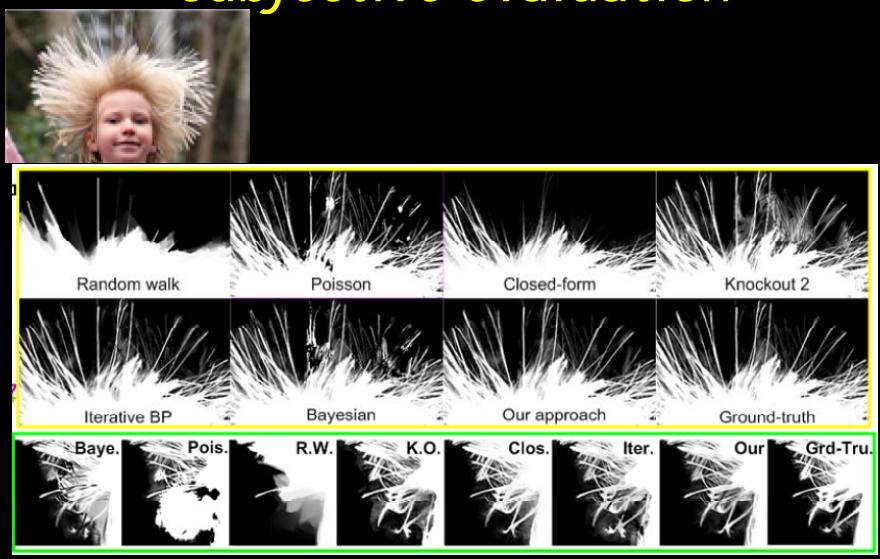
Quantitative evaluation



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

New evaluation (CVPR 2009)

- <http://www.alphamatting.com/>

Method	SAD	MSE	Grad.	Conn.
Closed-form [13]	1.3	1.4	1.5	2.0
Robust matting [23]	1.9	1.8	1.7	3.4
Random walk [8]	3.3	3.2	3.5	1.3
Easy matting [9]	4.0	4.4	4.2	3.7
Bayesian matting [6]	4.5	4.3	4.3	5.0
Poisson matting [20]	5.9	5.9	6.0	5.6

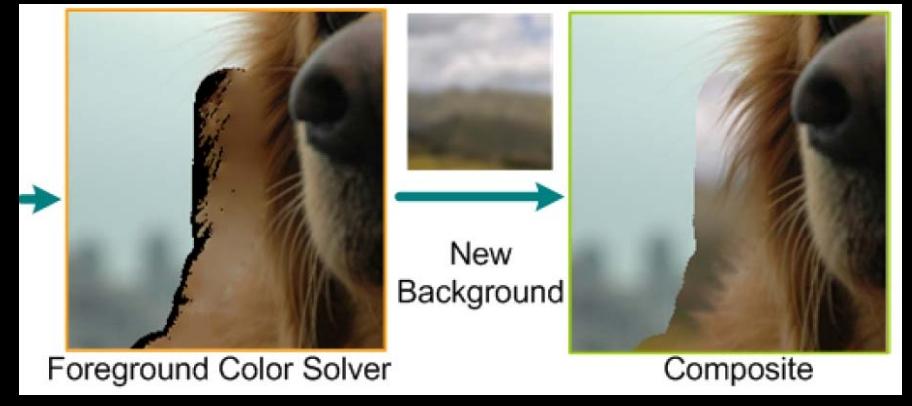
Soft scissor

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

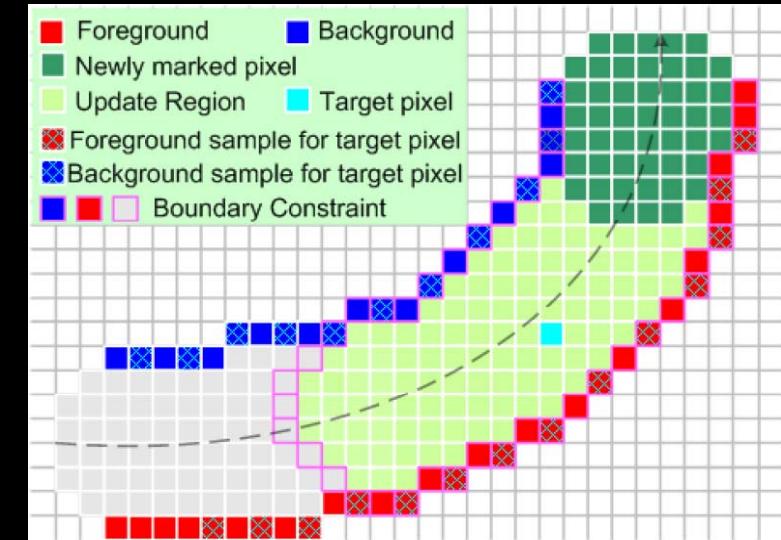
Flowchart



Flowchart



Soft scissor



Demo (Power Mask)



Outline

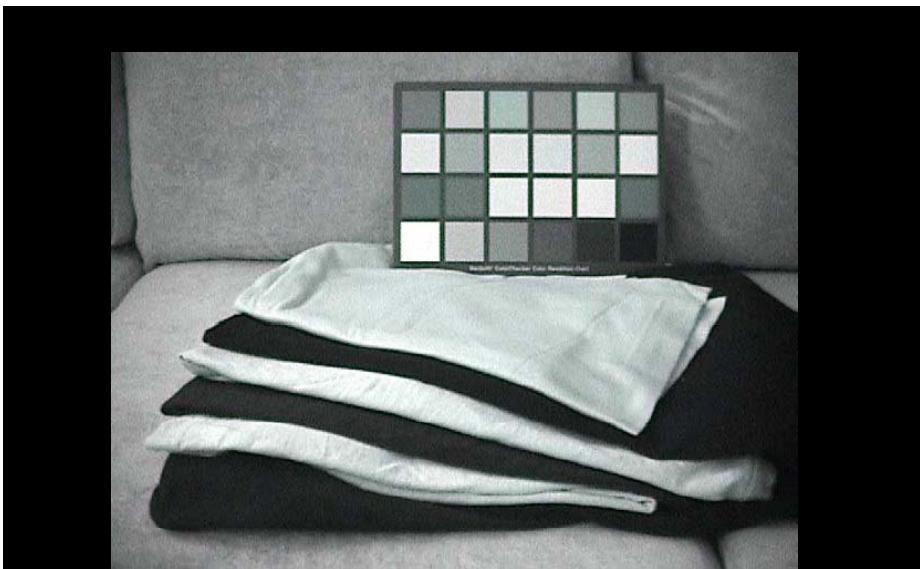
- Traditional matting and compositing
- The matting problem
- Bayesian matting and extensions
- Matting with less user inputs
- **Matting with multiple observations**
- Beyond the compositing equation*
- Conclusions

Matting with multiple observations

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



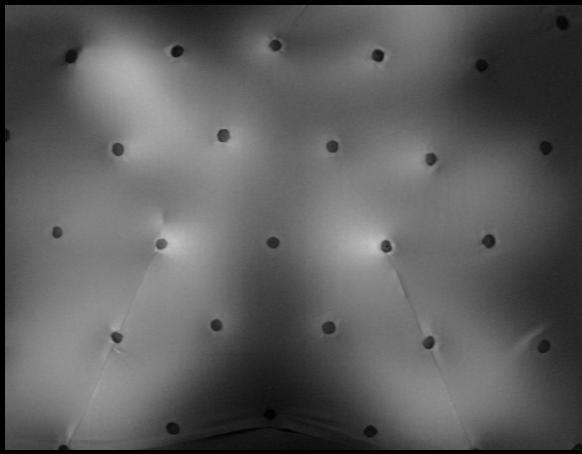
Invisible lights (Infared)



Invisible lights (Infared)



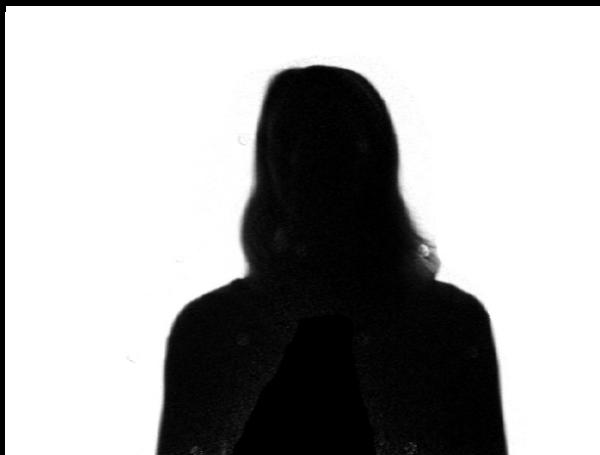
Invisible lights (Infared)



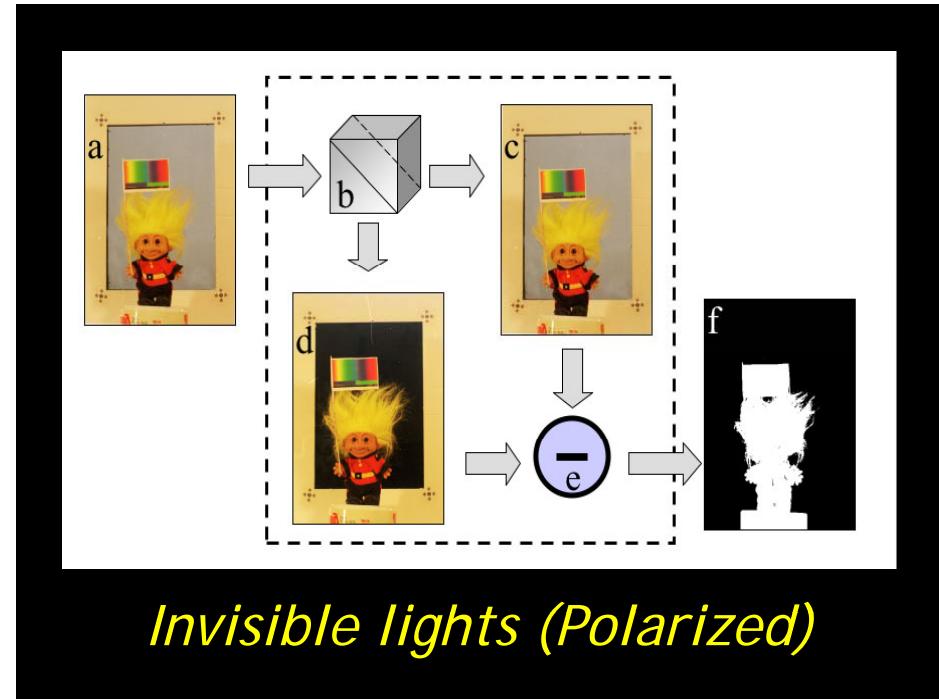
Invisible lights (Infared)



Invisible lights (Infared)



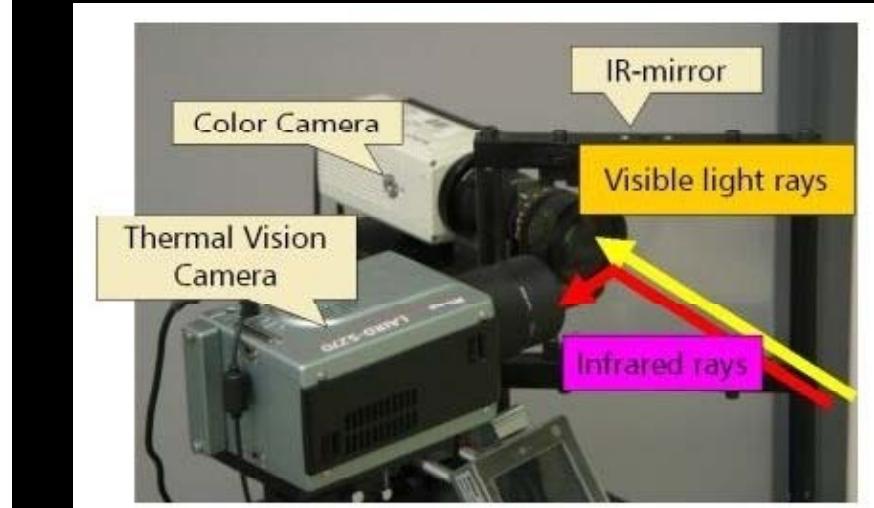
Invisible lights (Infared)



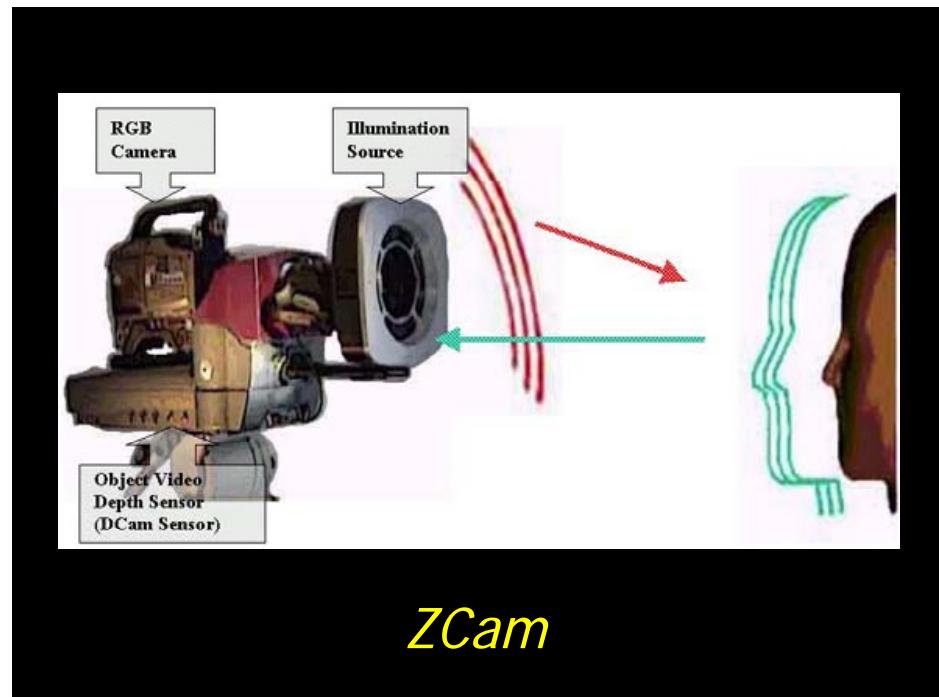
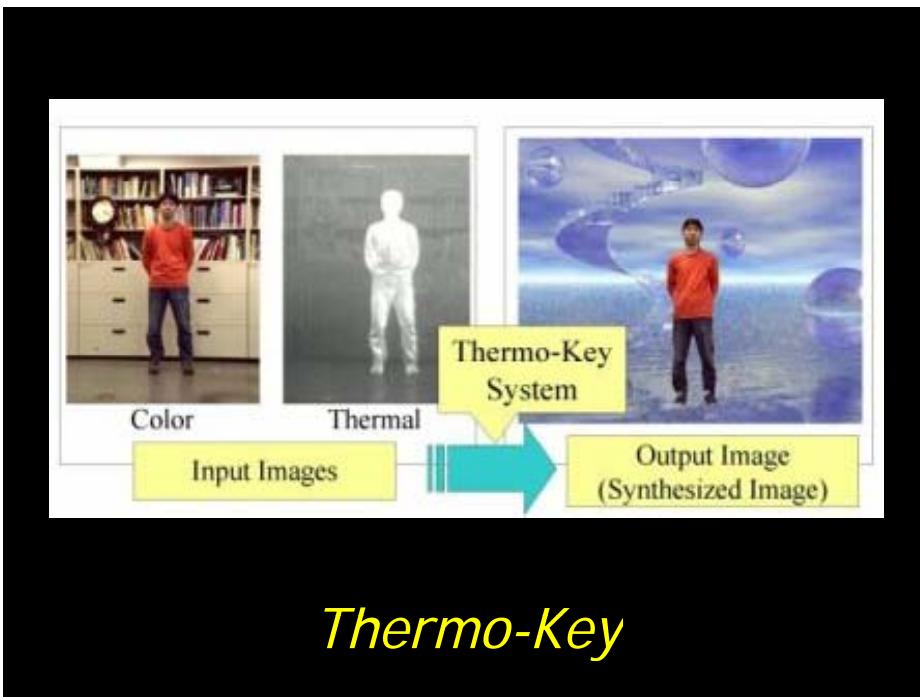
Invisible lights (Polarized)

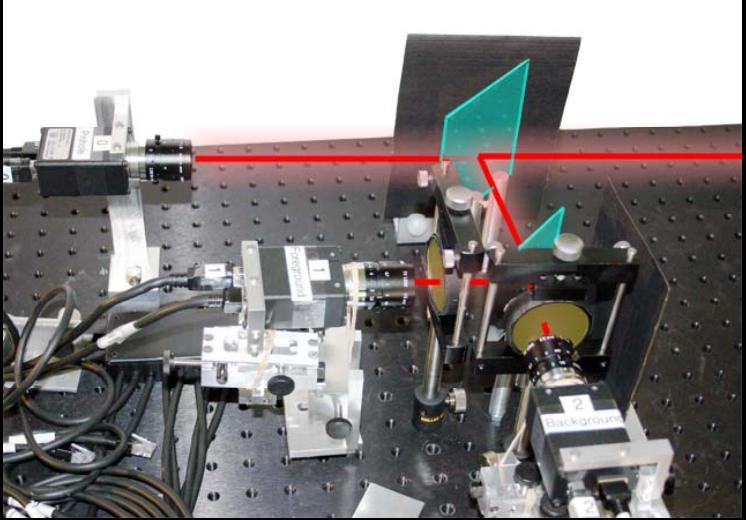


Invisible lights (Polarized)

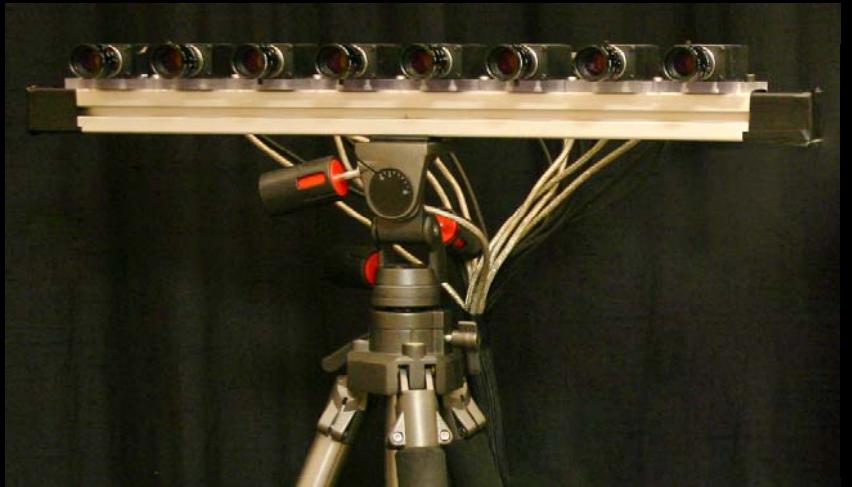


Thermo-Key



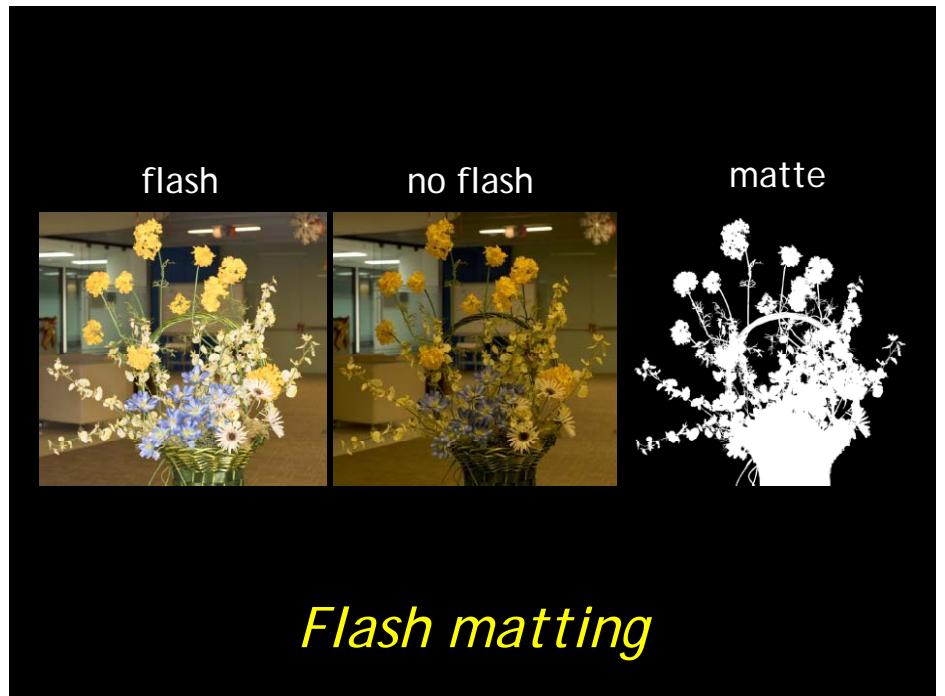


Defocus matting



[video](#)

Matting with camera arrays



Flash matting

$$\begin{aligned} I &= \alpha F + (1 - \alpha) B, \\ I^f &= \alpha F^f + (1 - \alpha) B^f, \end{aligned}$$

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.

$$\begin{aligned} &\arg \max_{\alpha, F'} L(\alpha, F' | I') \\ &= \arg \max_{\alpha, F'} \{L(I' | \alpha, F') + L(F') + L(\alpha)\} \\ L(I' | \alpha, F') &= -||I' - \alpha F'|| / \sigma_{I'}^2, \\ L(F') &= -(F' - \bar{F'})^T \Sigma_{F'}^{-1} (F' - \bar{F'}) \end{aligned}$$

Flash matting



Foreground flash matting

$$\begin{aligned} I &= \alpha F + (1 - \alpha) B \\ I' &= \alpha F' \end{aligned}$$

$$\begin{aligned} &\arg \max_{\alpha, F, B, F'} L(\alpha, F, B, F' | I, I') \\ &= \arg \max_{\alpha, F, B, F'} \{L(I | \alpha, F, B) + L(I' | \alpha, F') + \\ &\quad L(F) + L(B) + L(F') + L(\alpha)\} \end{aligned}$$

Joint Bayesian flash matting

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

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

Joint Bayesian flash matting

flash



no flash



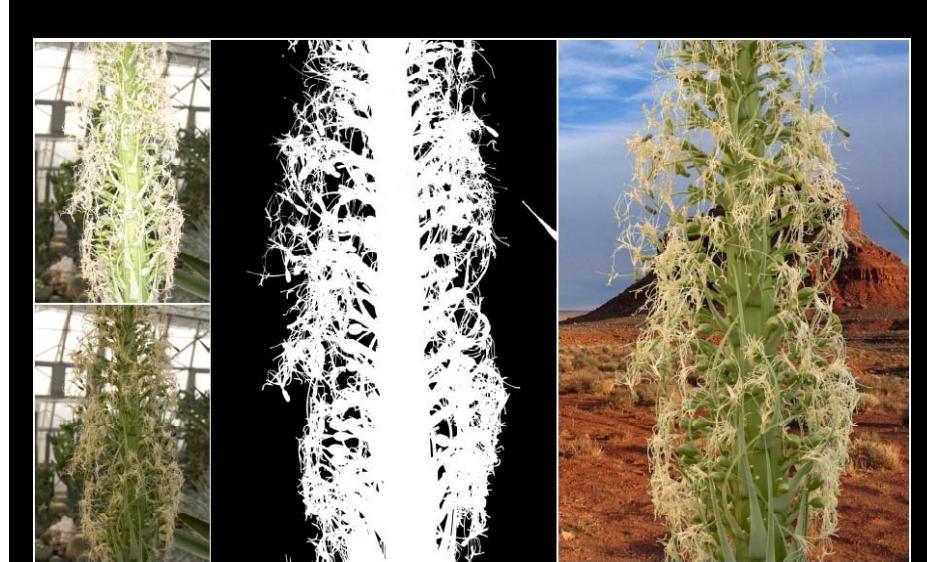
Comparison

foreground
flash matting

joint Bayesian
flash matting



Comparison



Flash matting

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**

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

Thanks for your attention!

*Shadow matting
and composting*

source scene



target background



blue screen image



target background



blue screen composite



target background



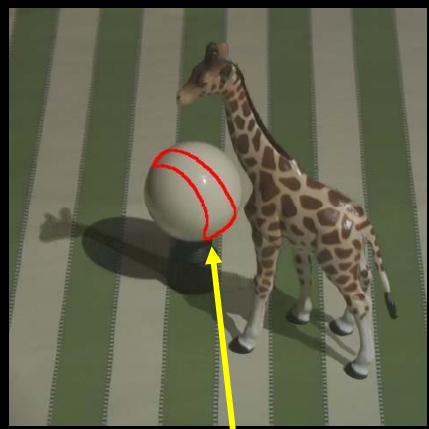
blue screen composite



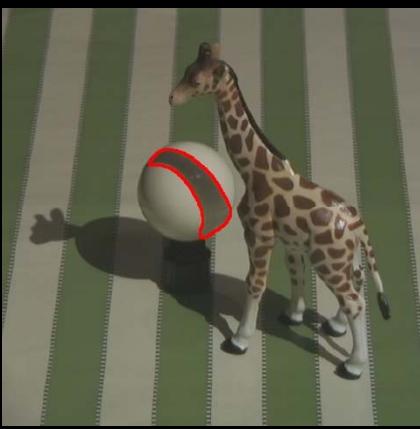
photograph



blue screen composite

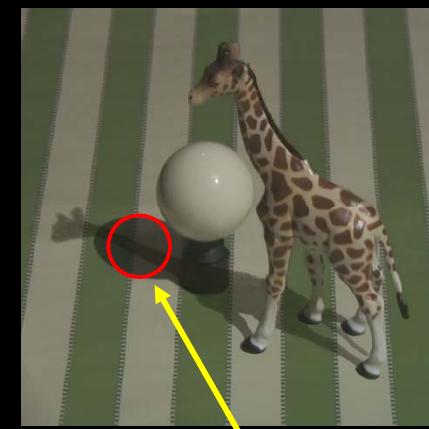


photograph

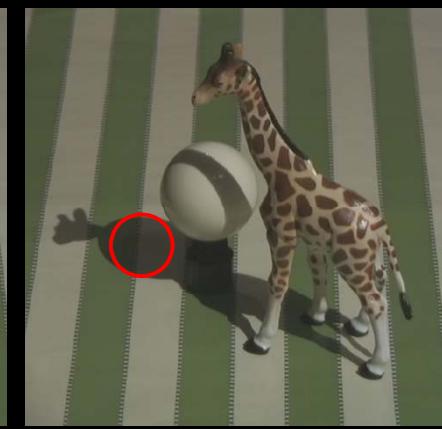


Geometric errors

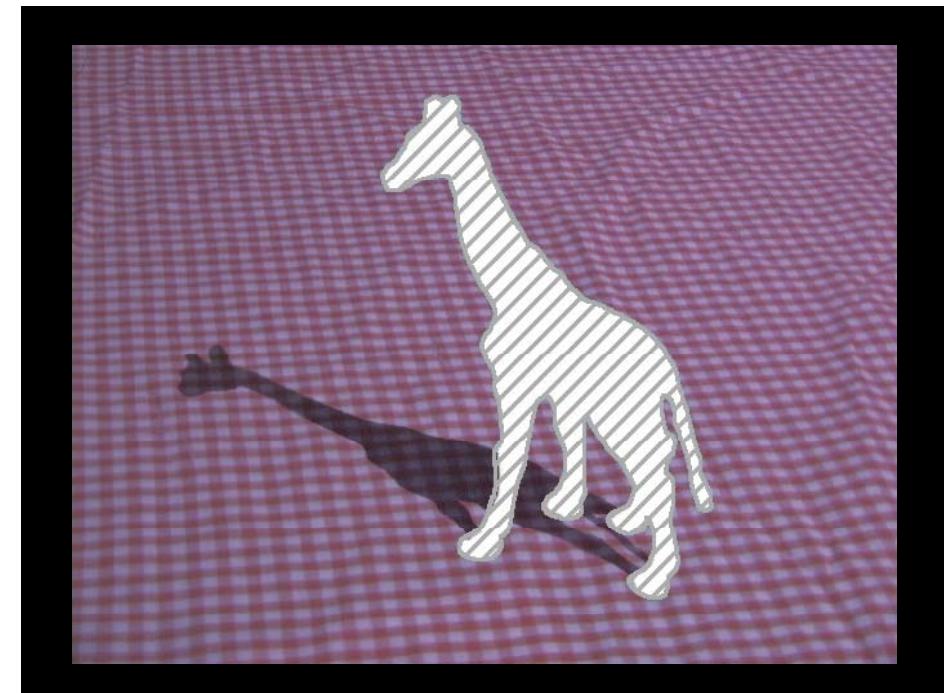
blue screen composite

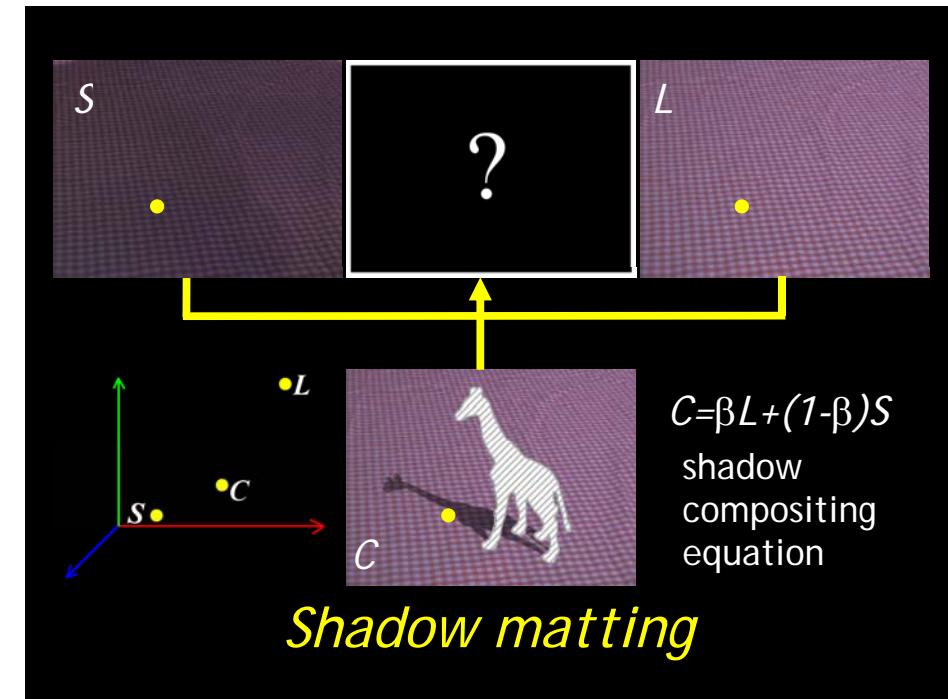
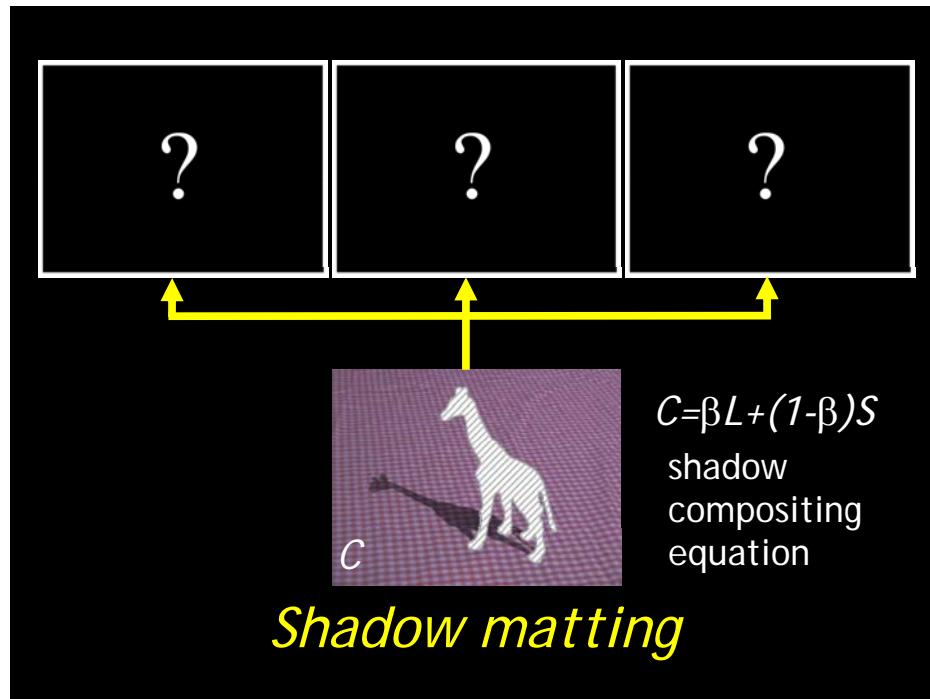
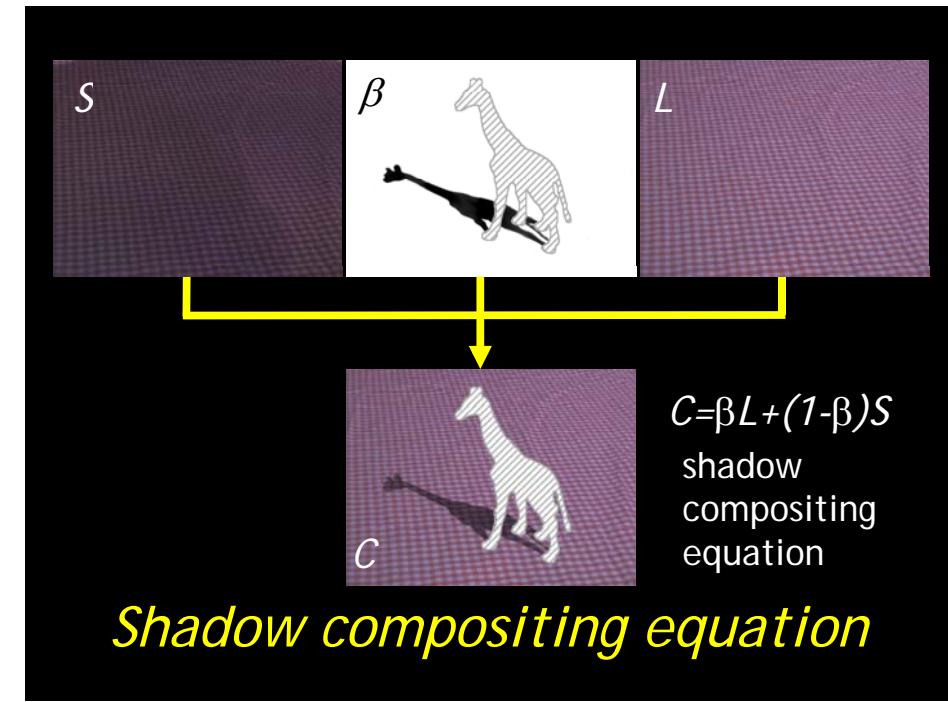
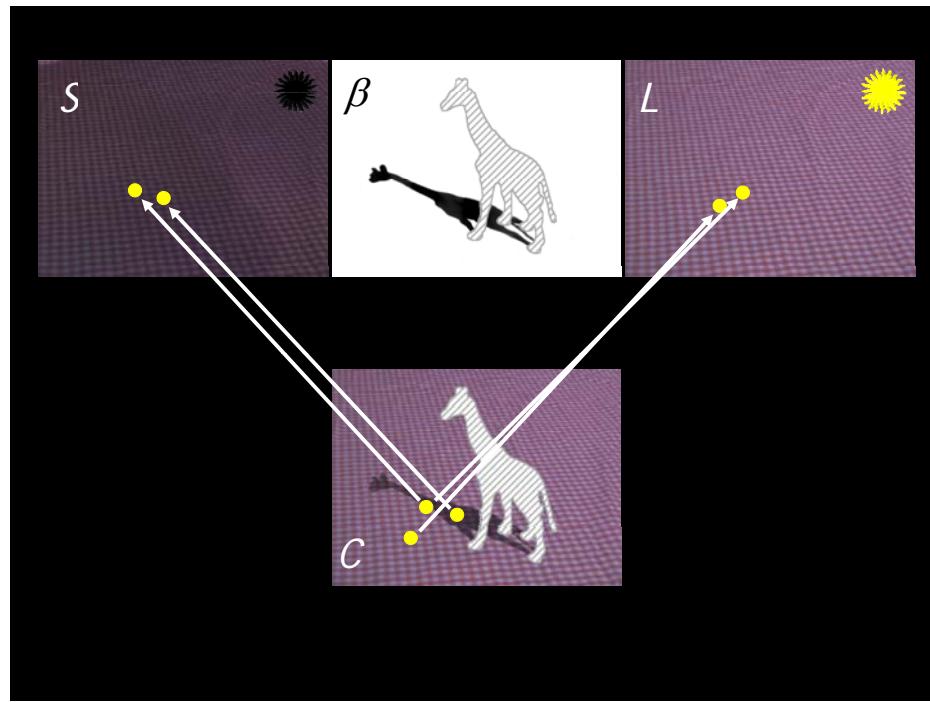


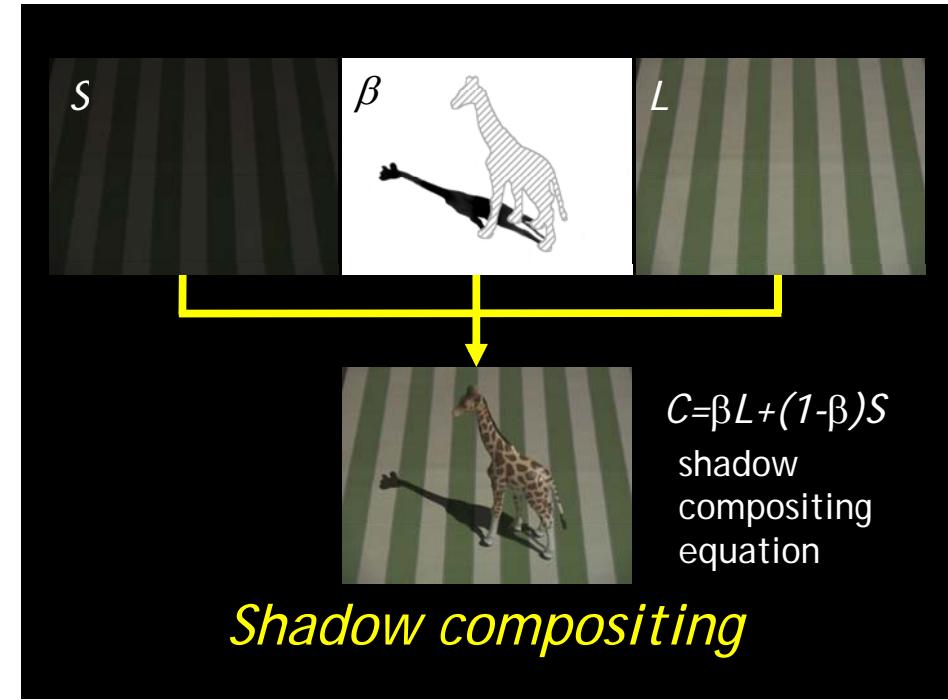
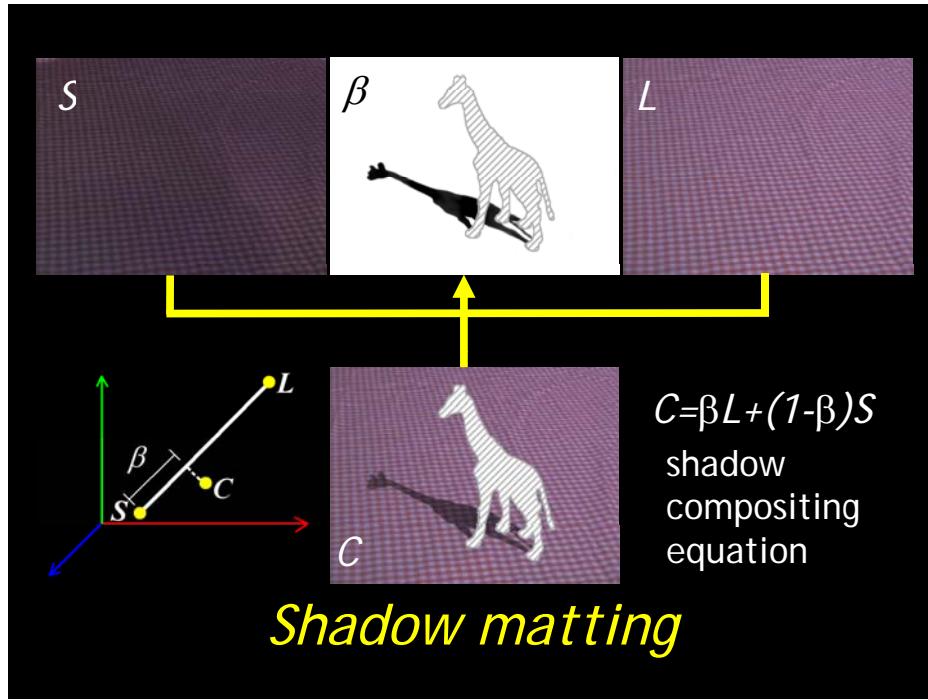
photograph

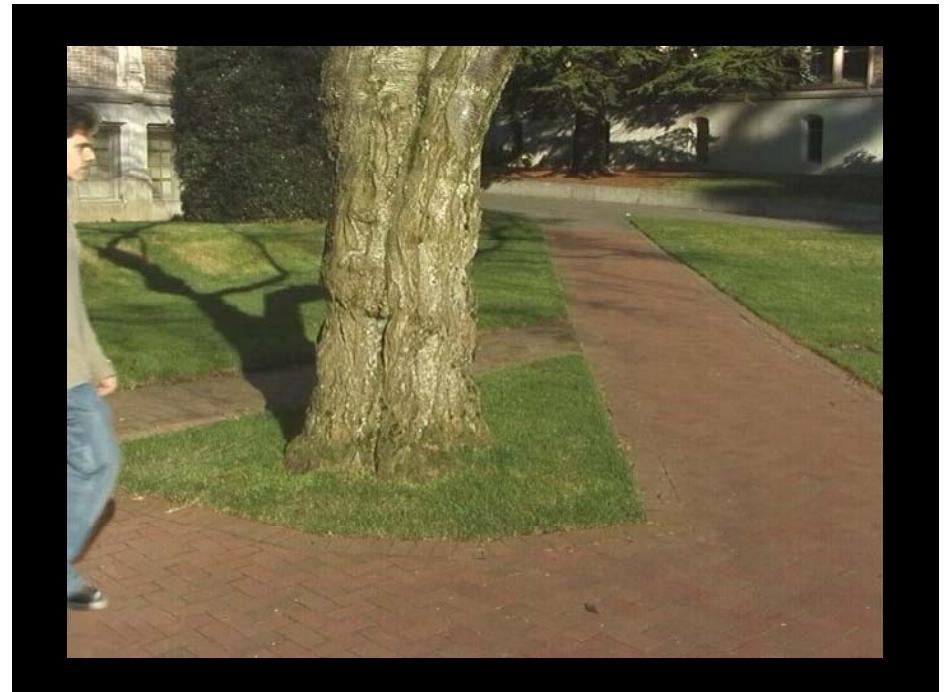


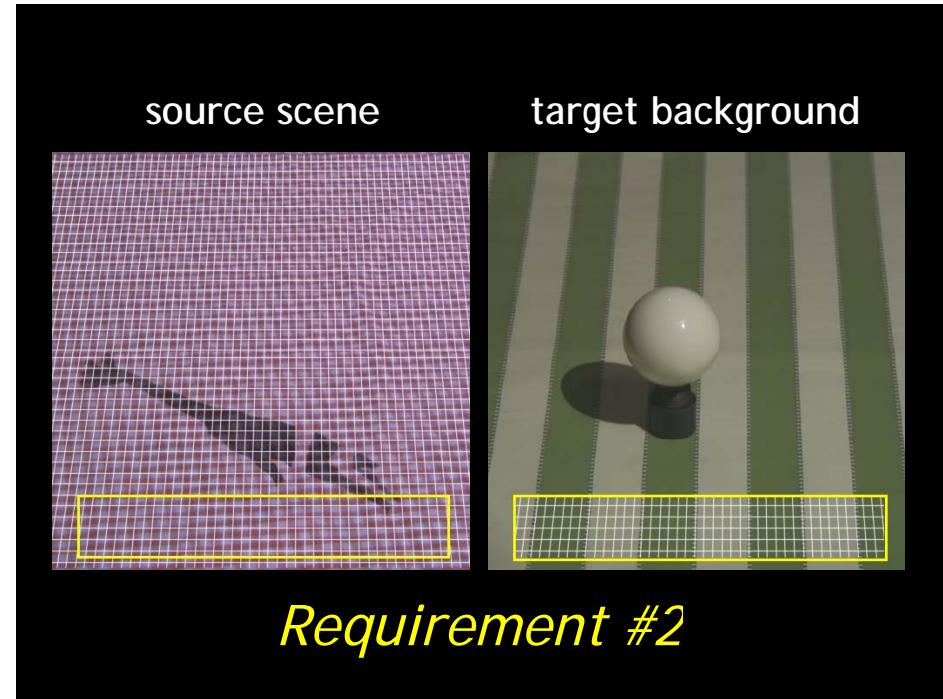
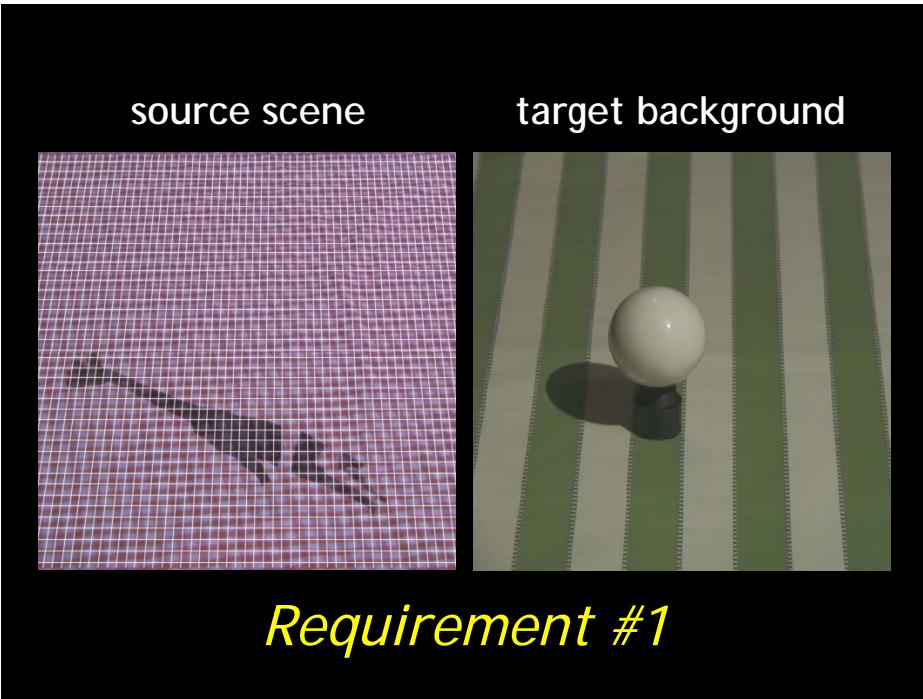
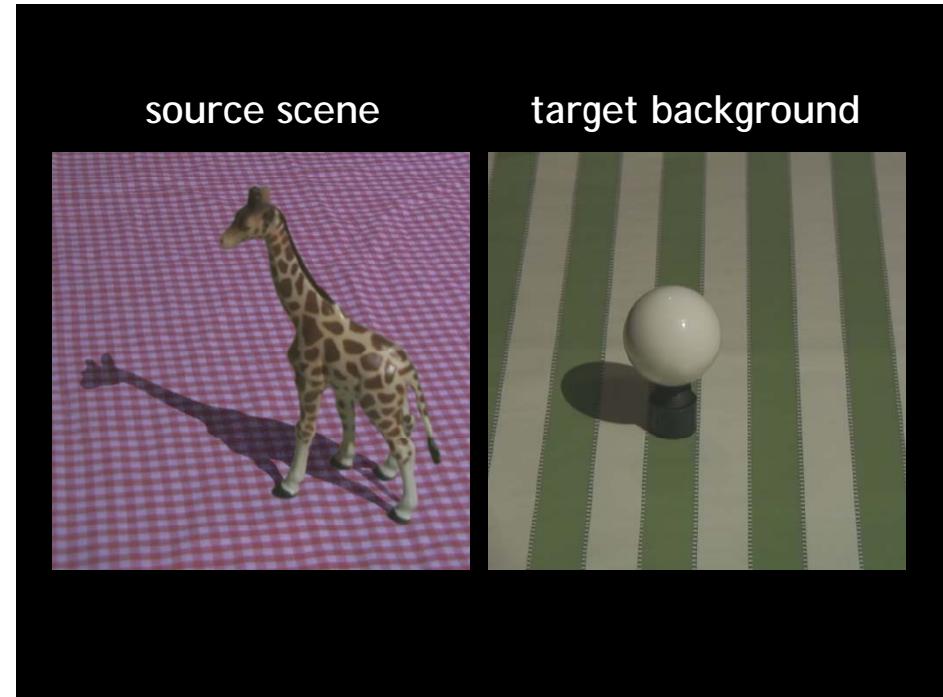
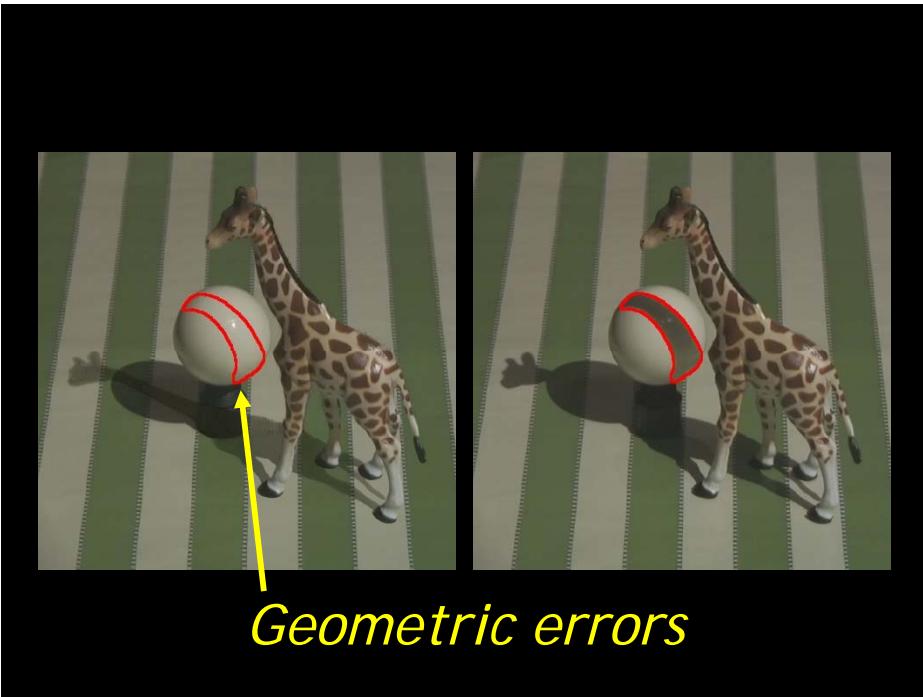
Photometric errors

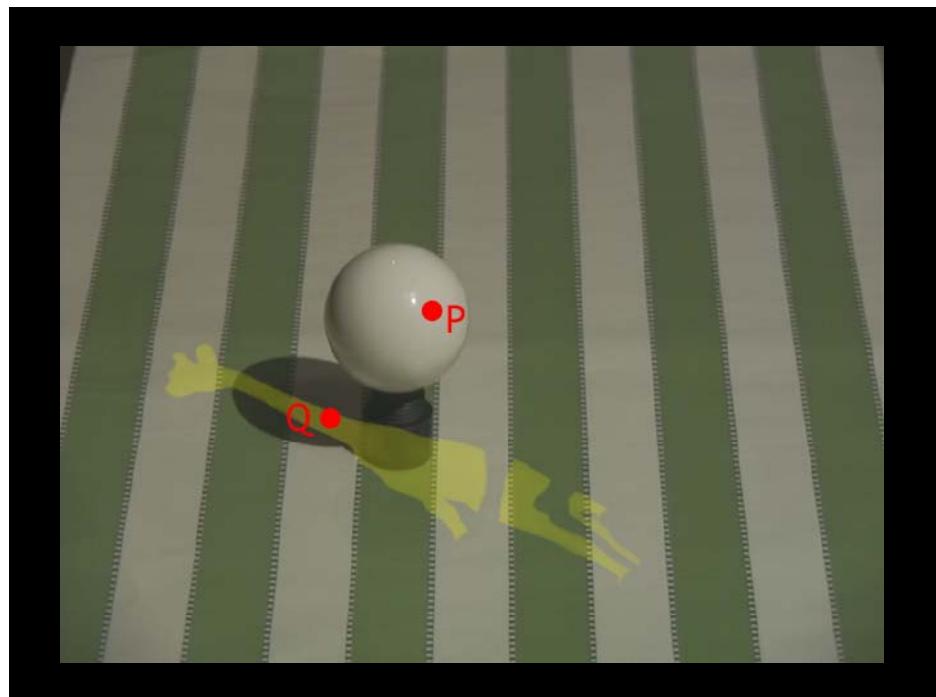
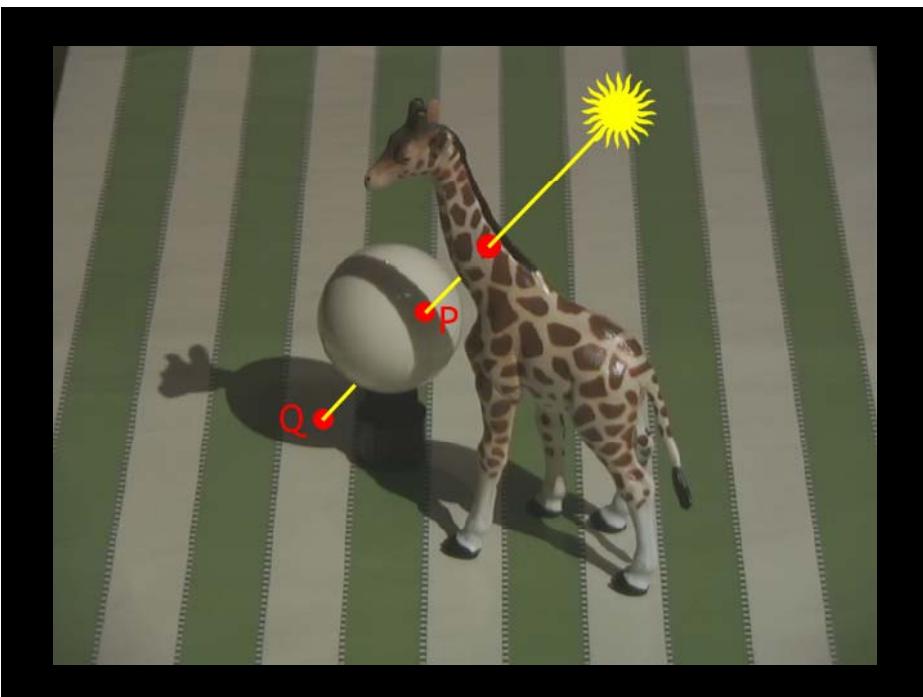
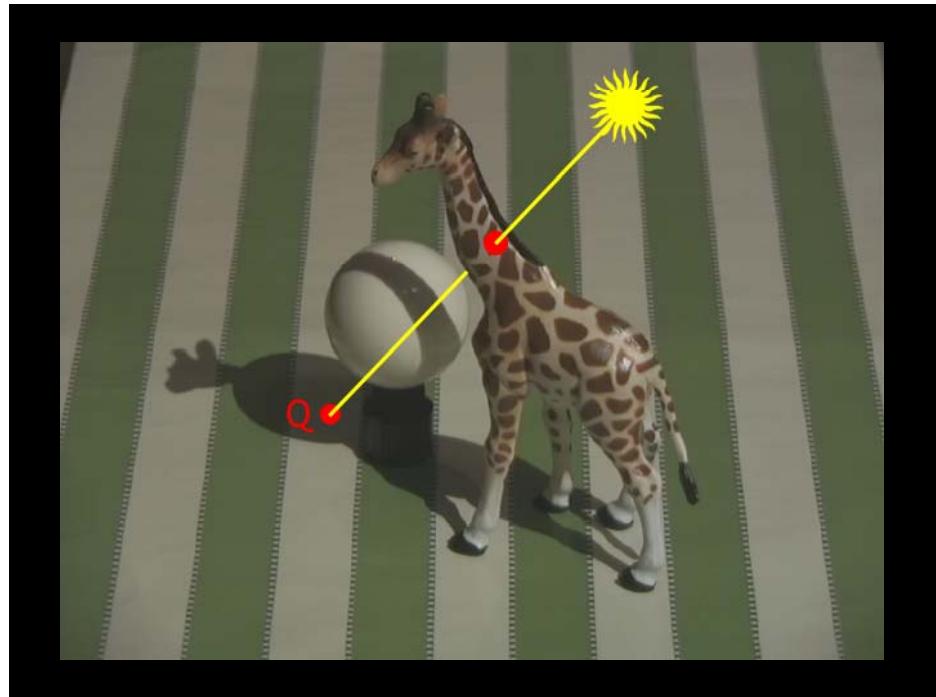
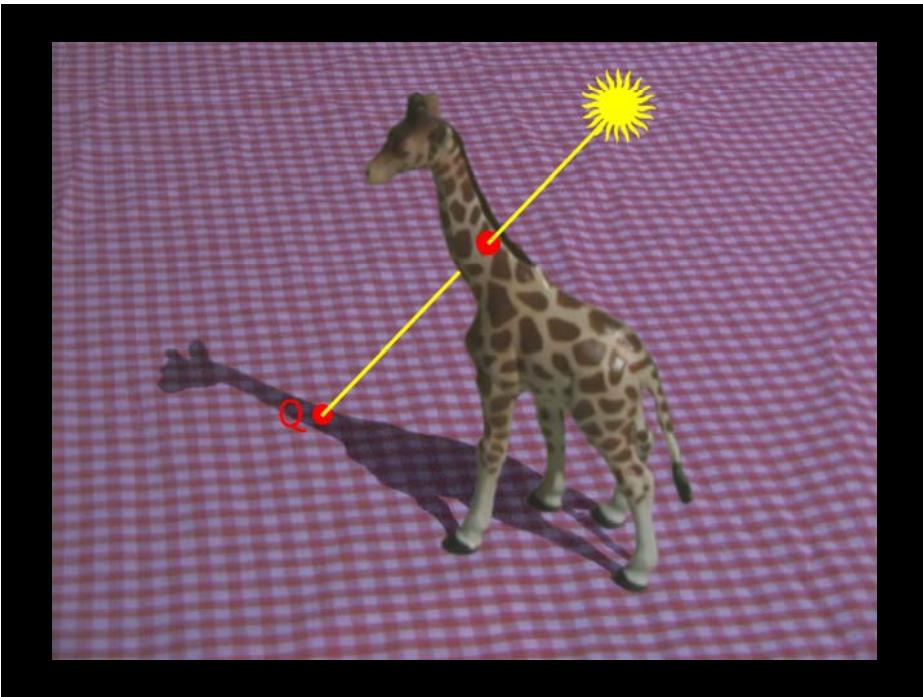


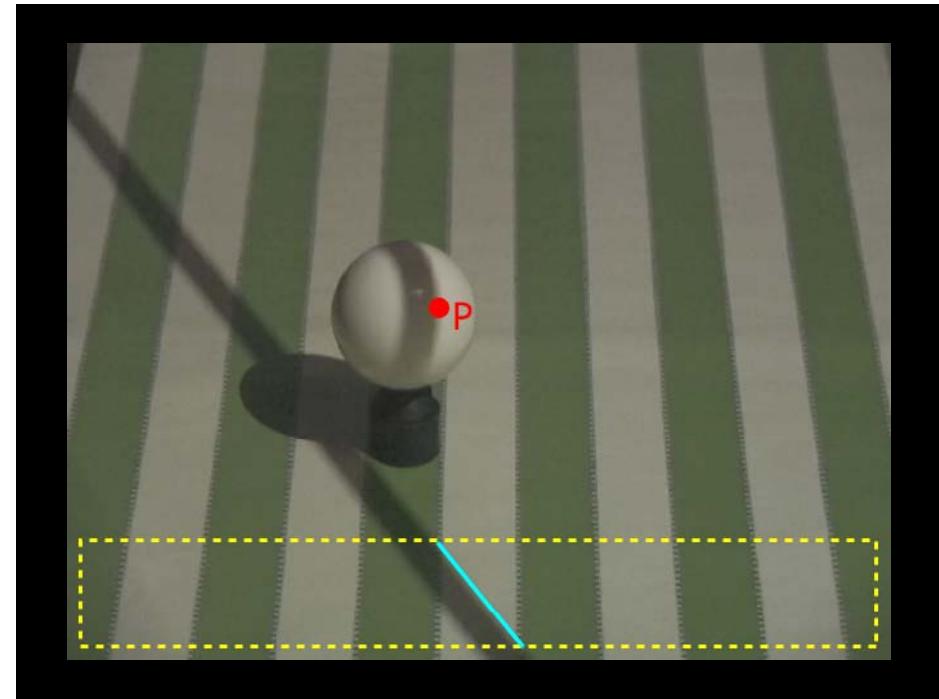
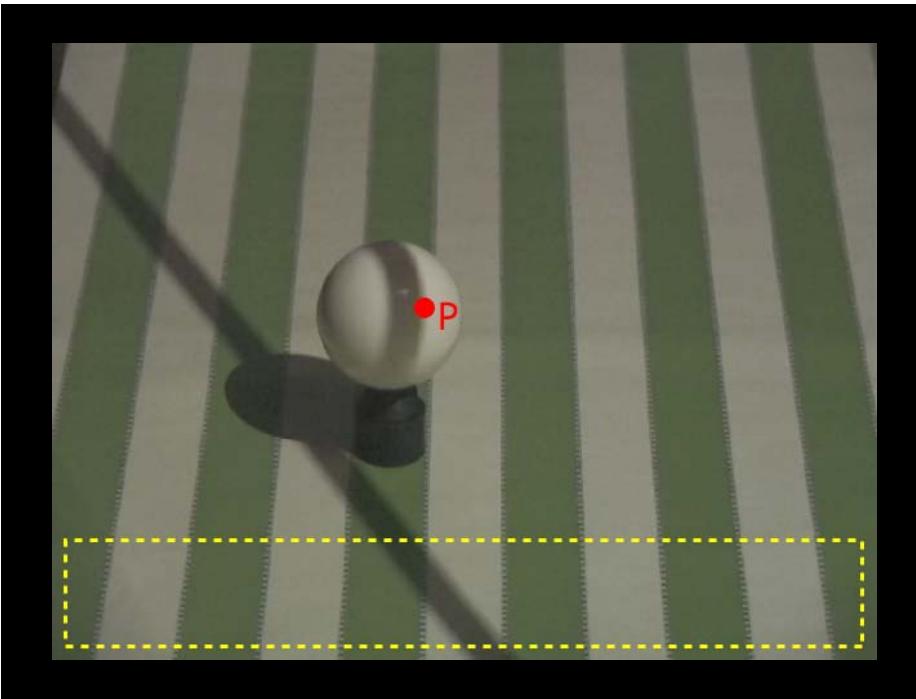
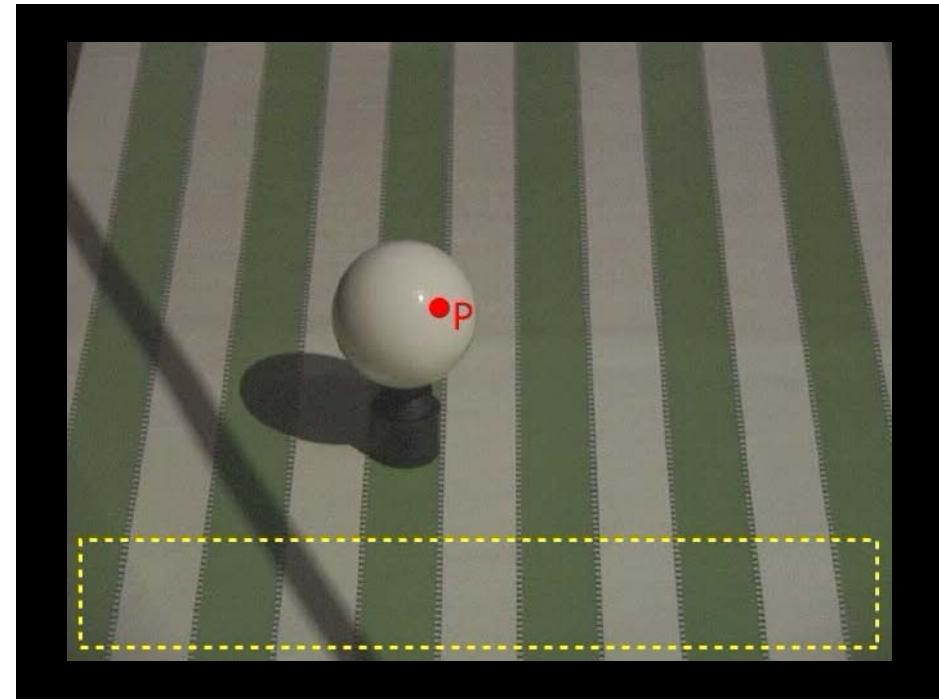
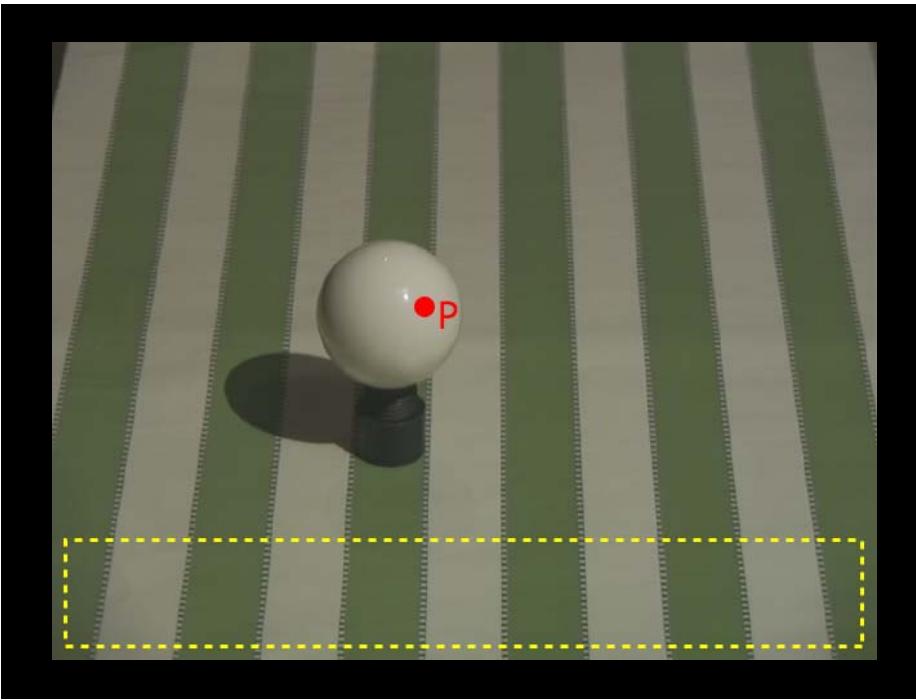


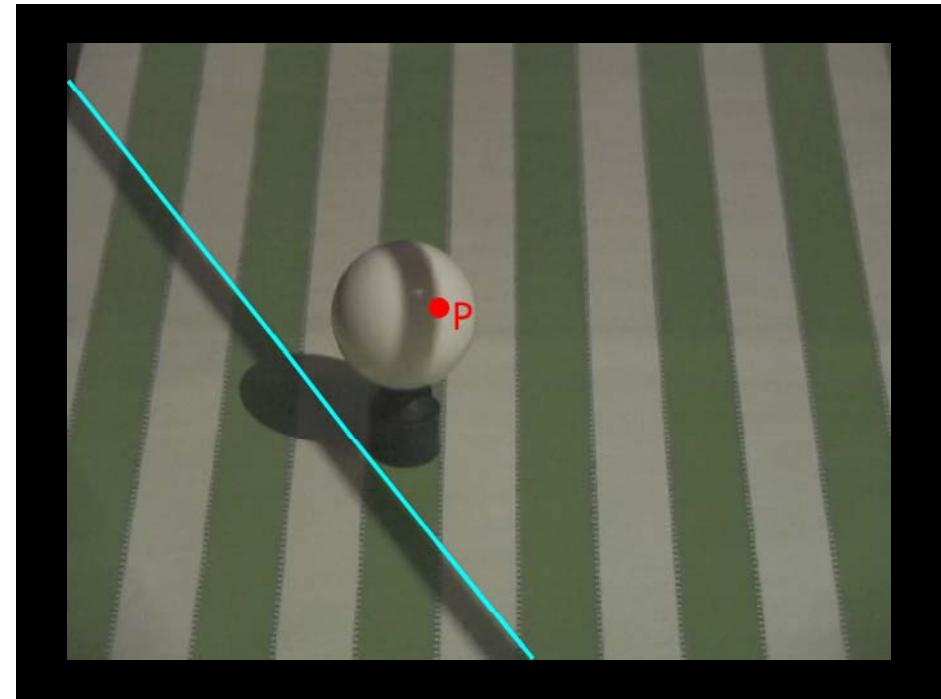
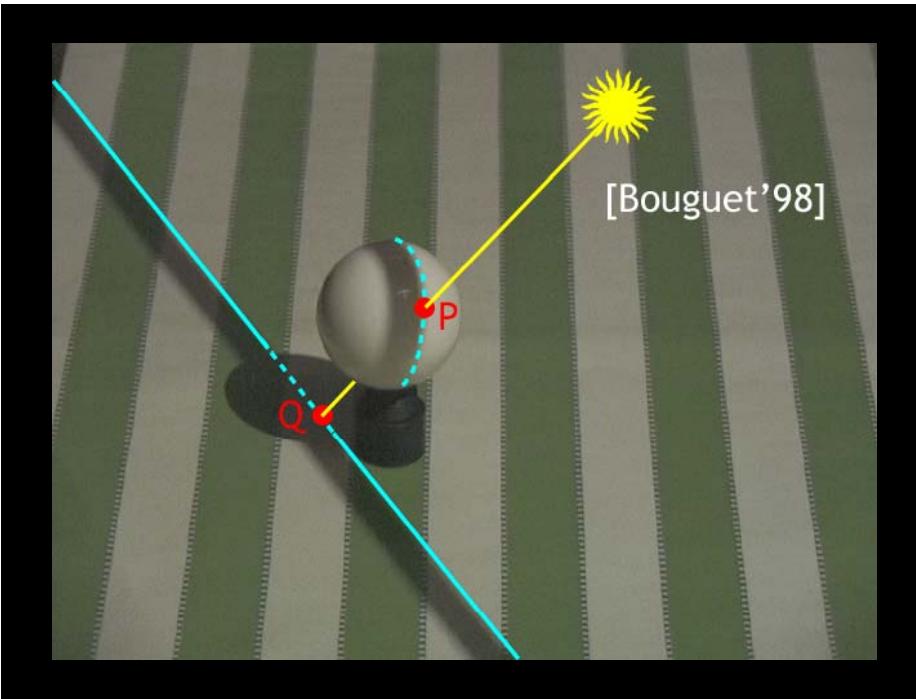
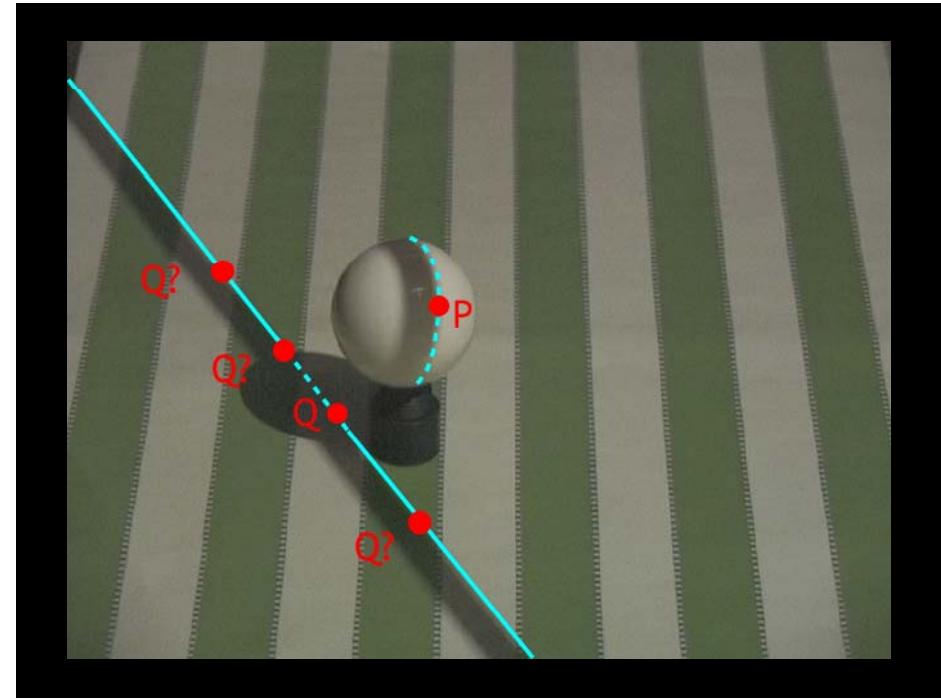
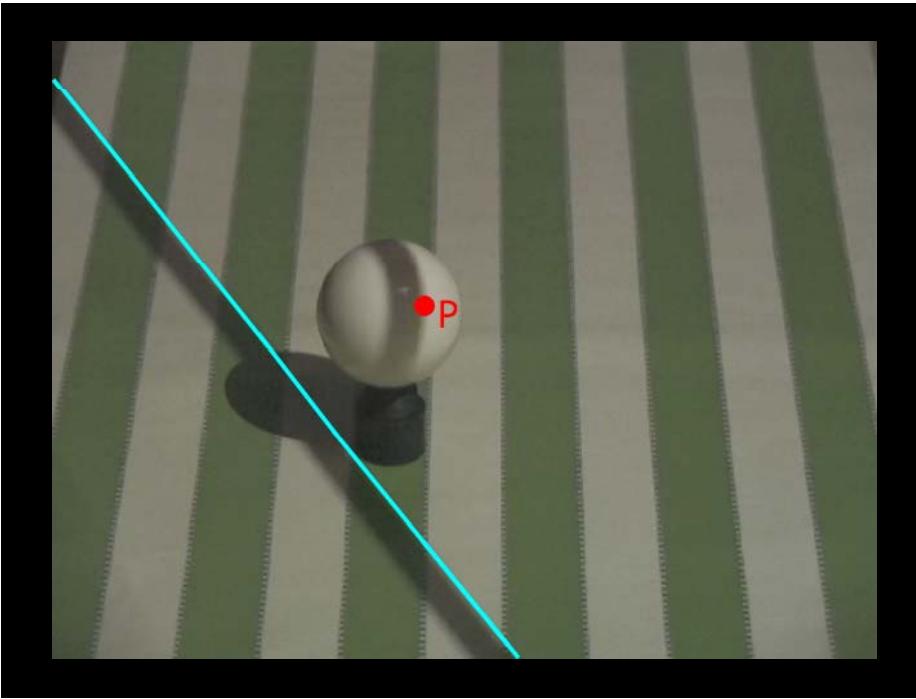


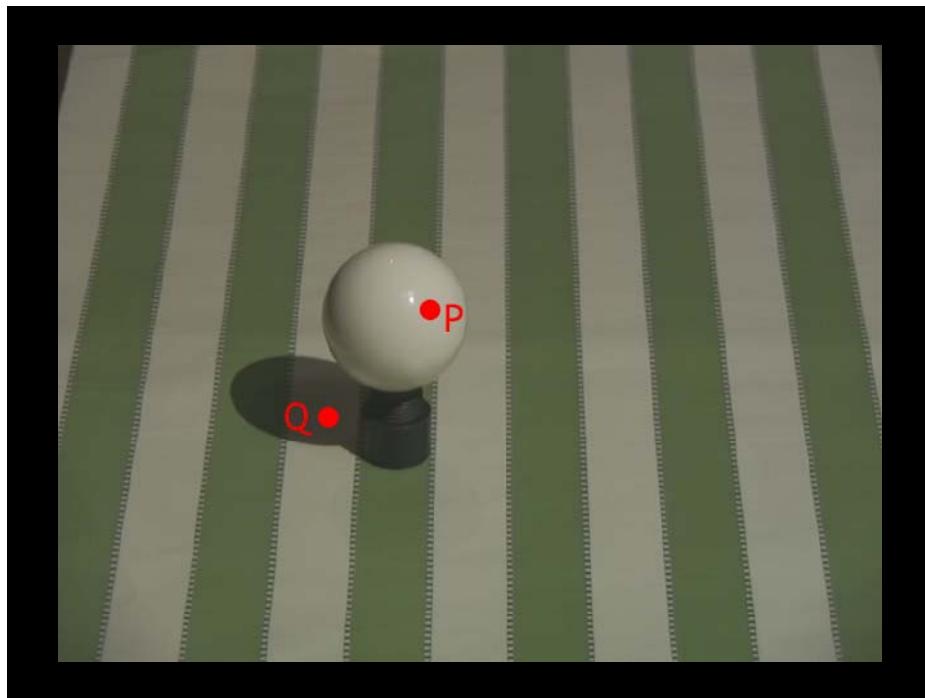
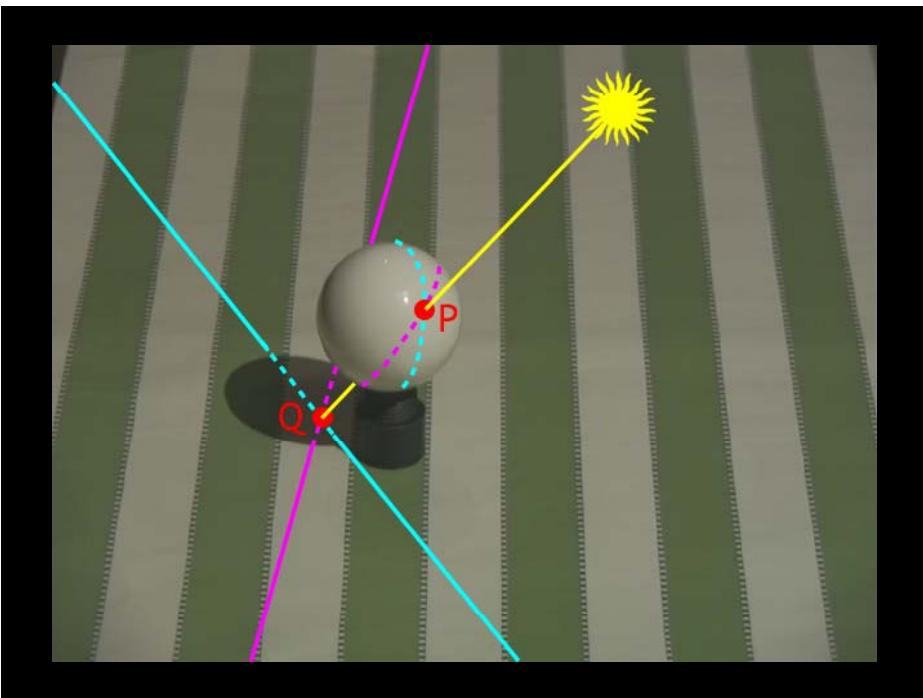
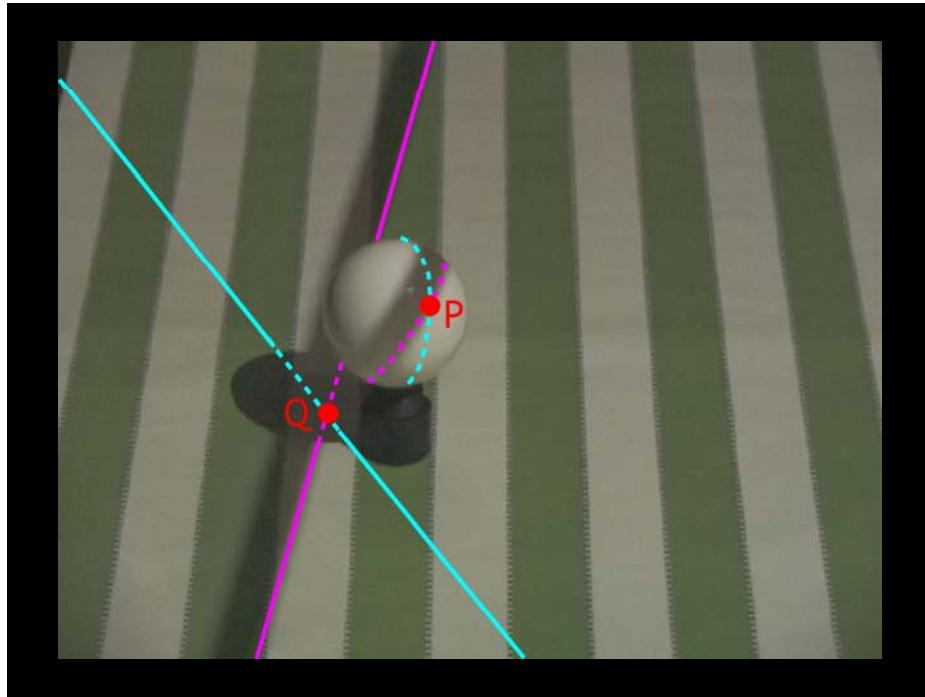
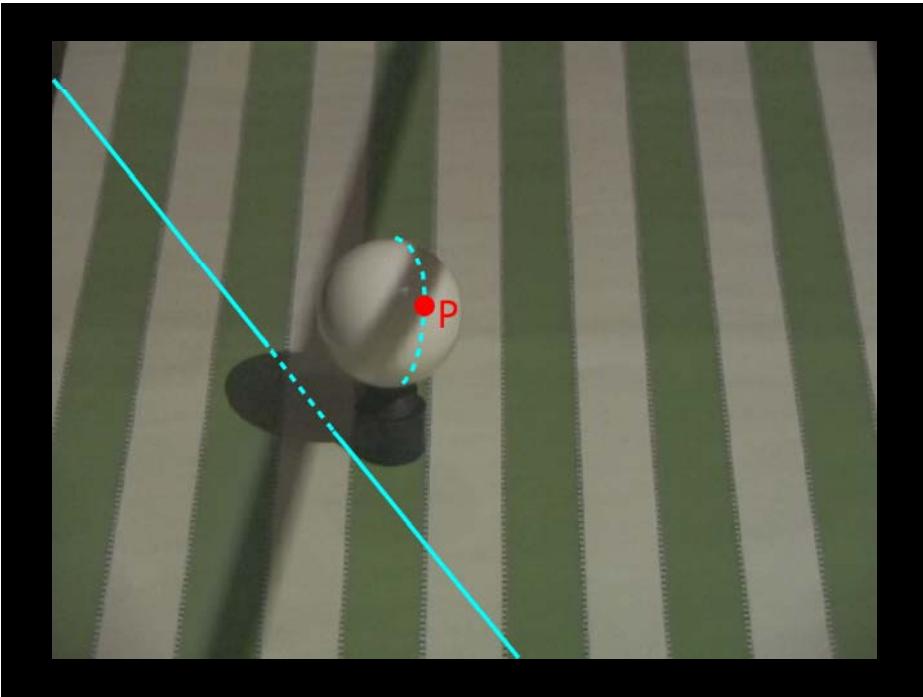


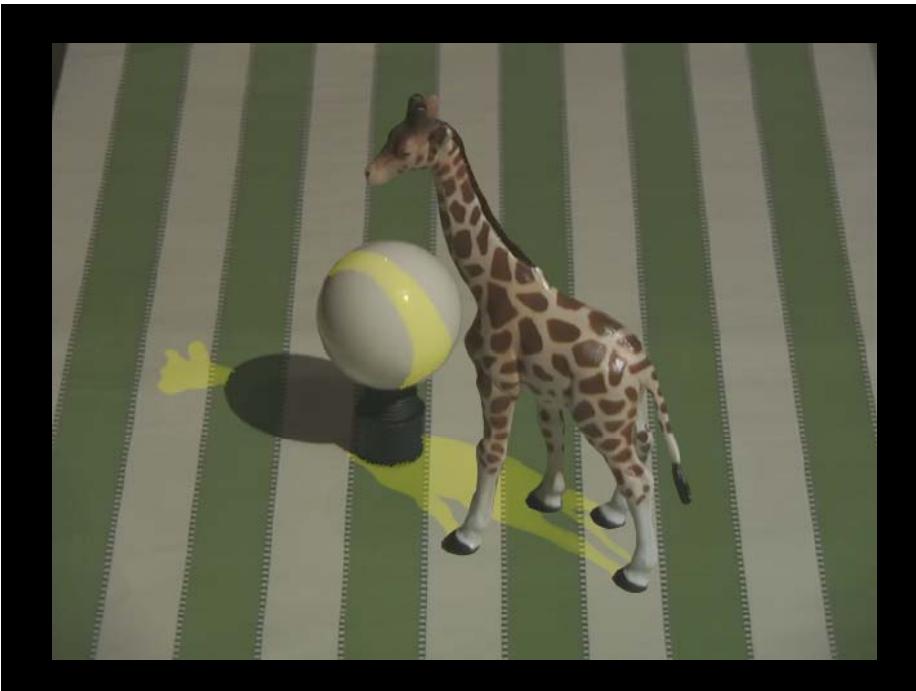
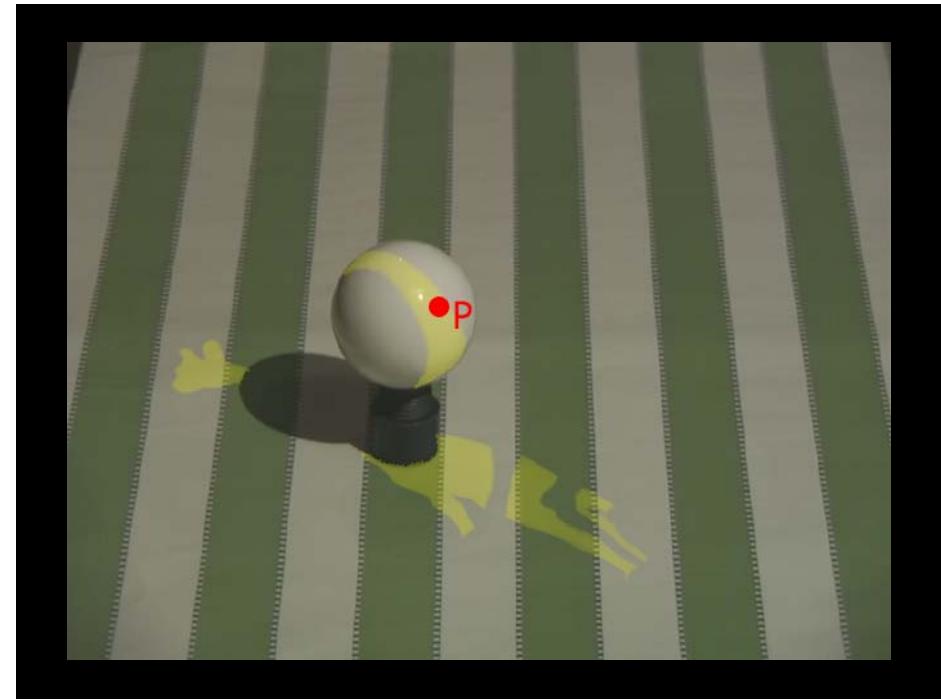
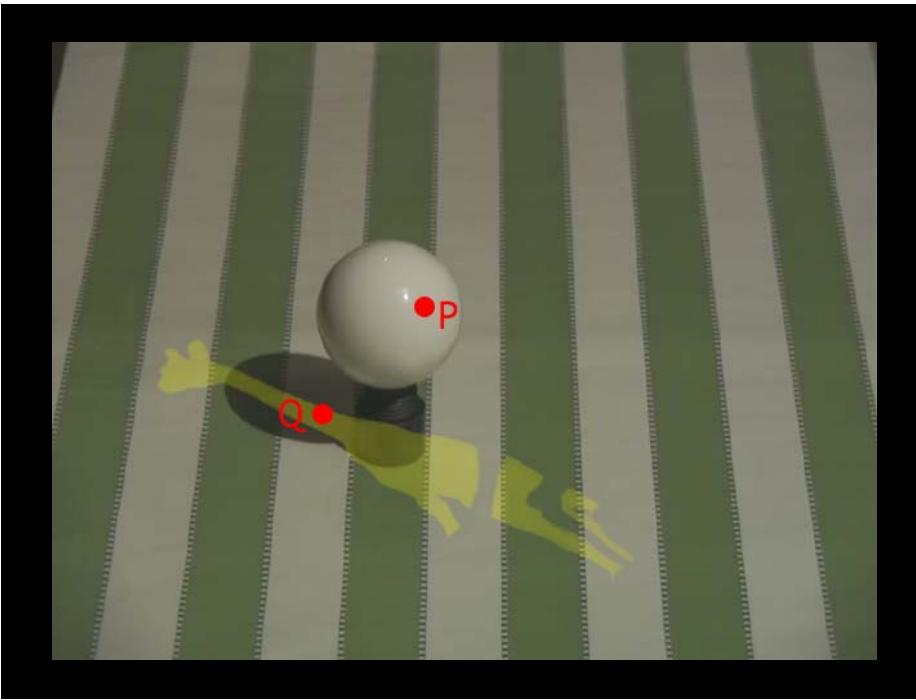


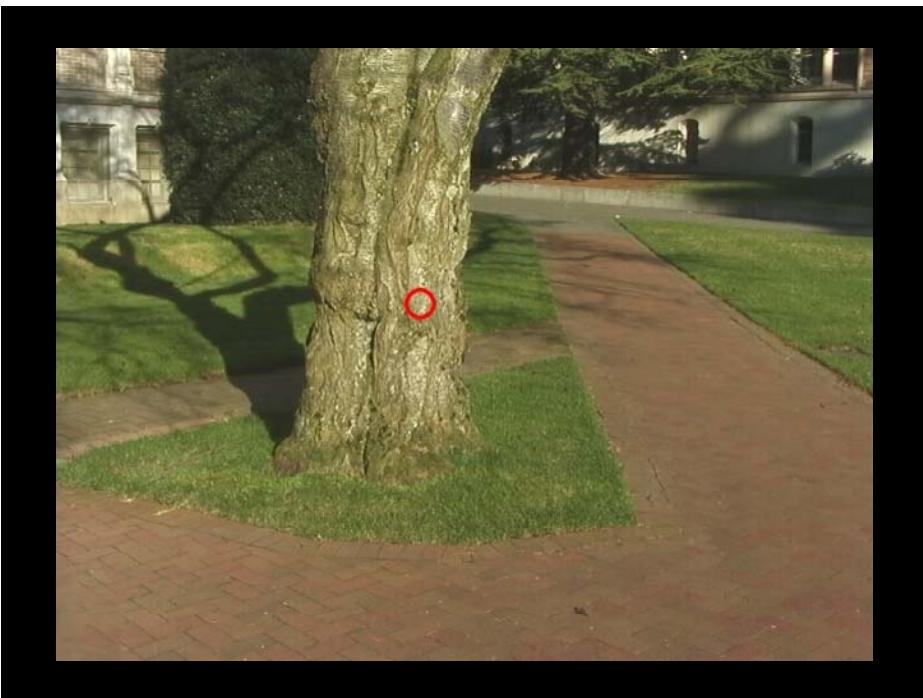
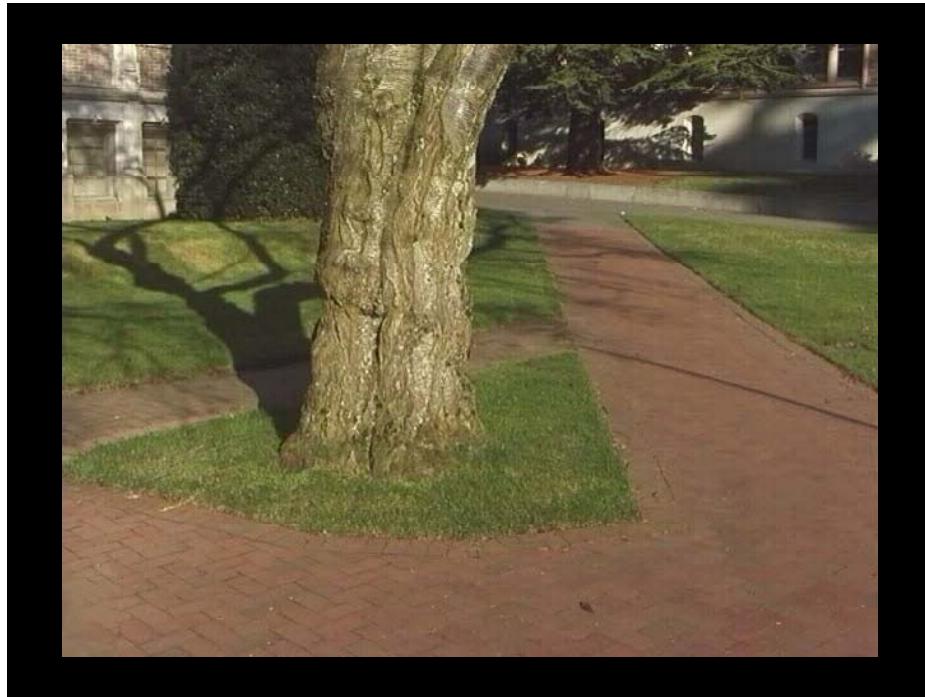
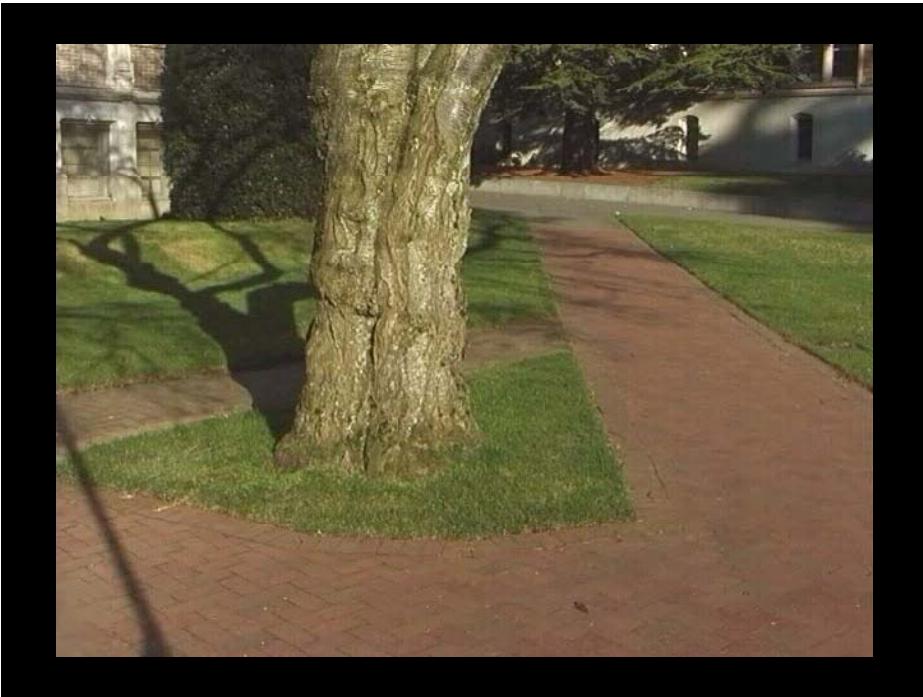


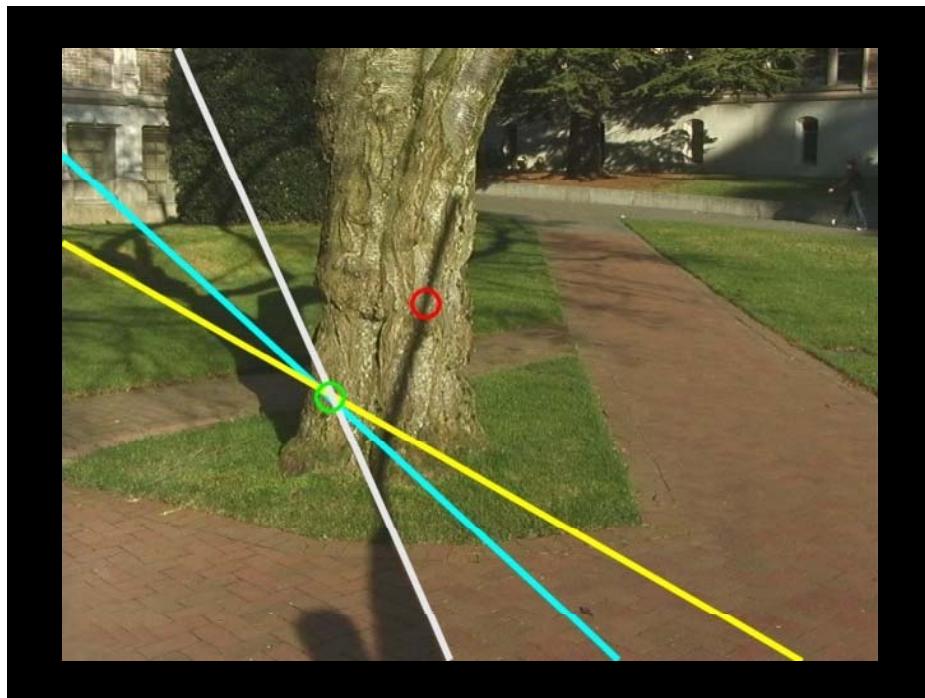
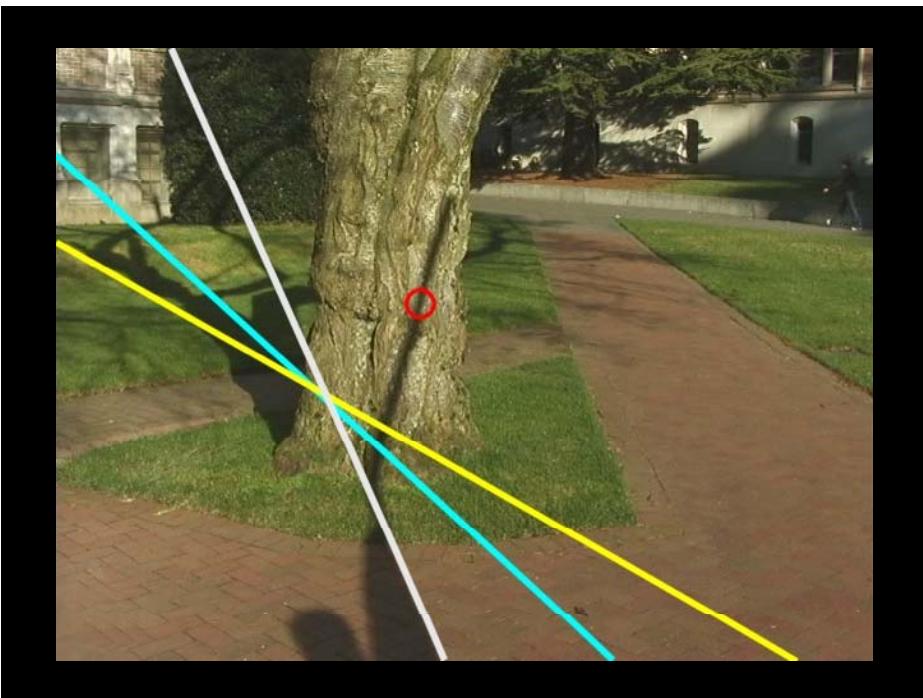
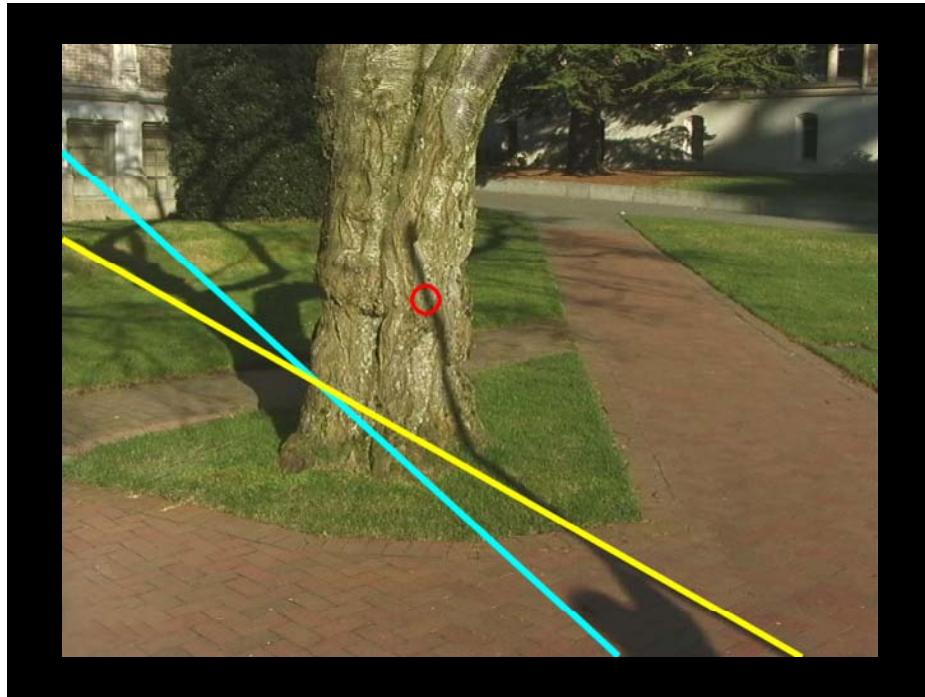
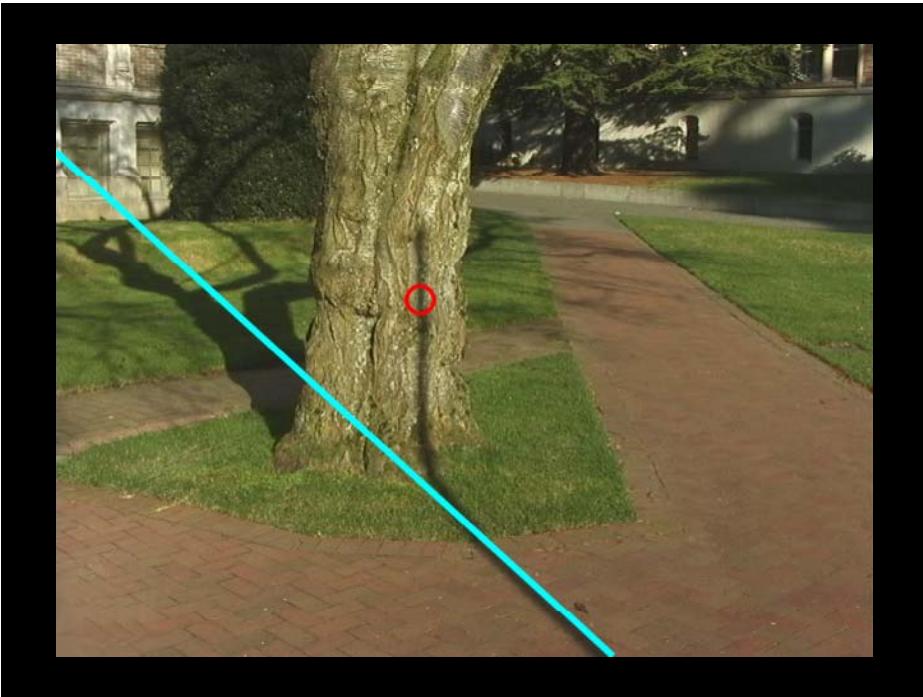


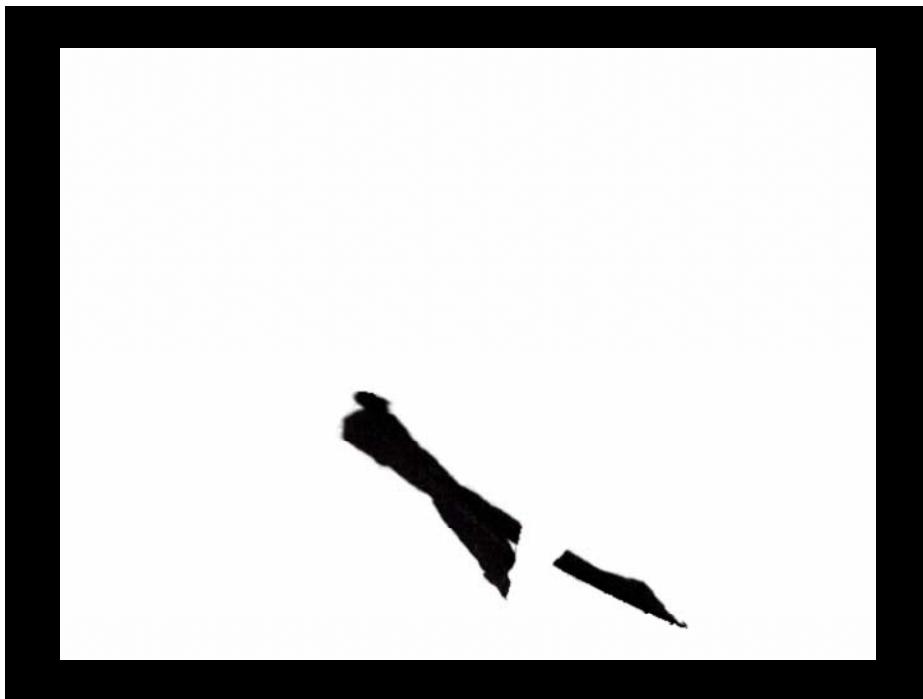
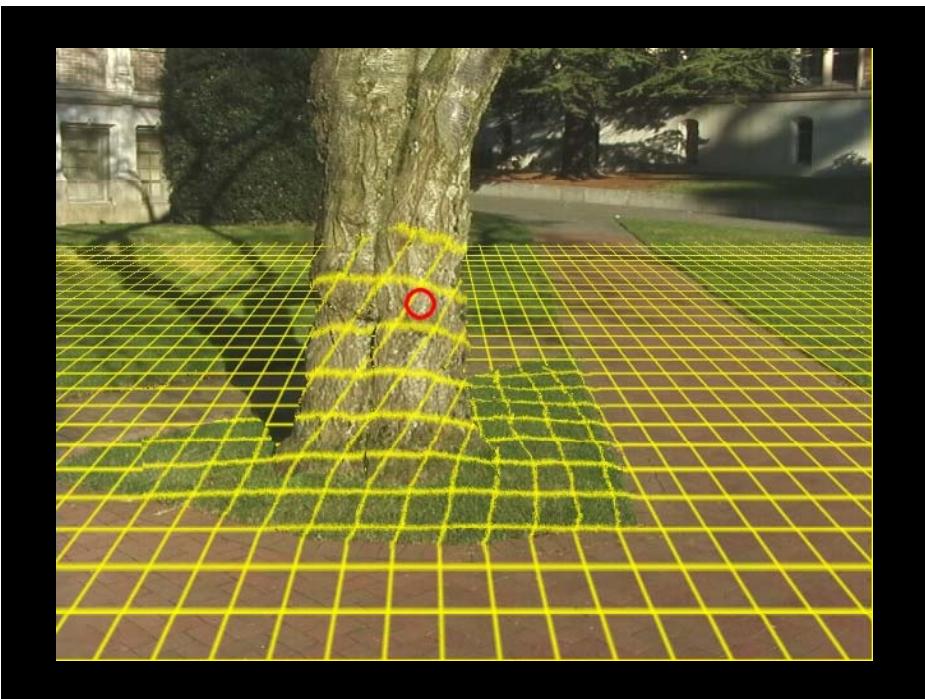
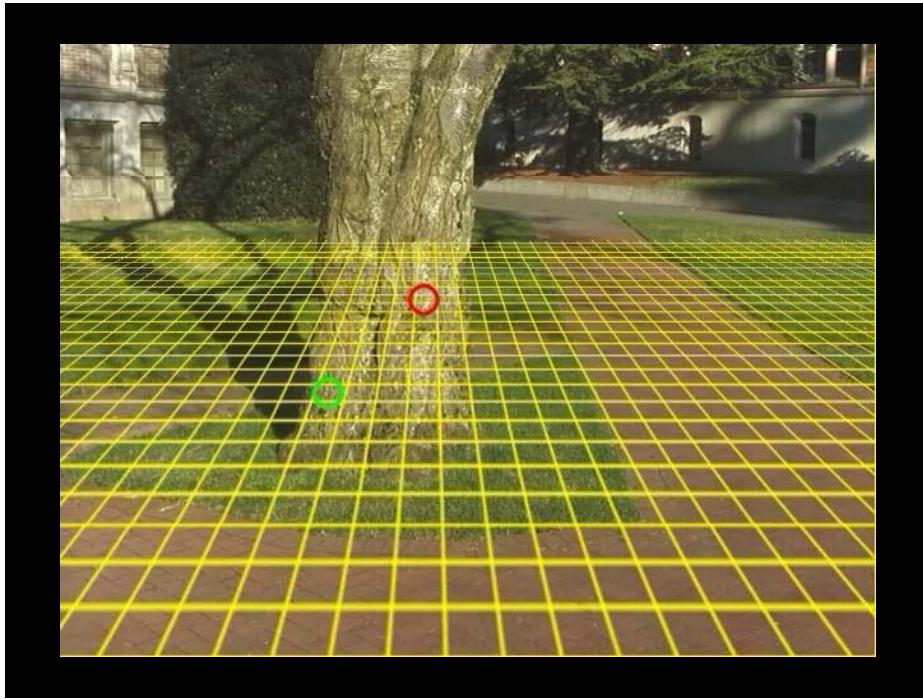
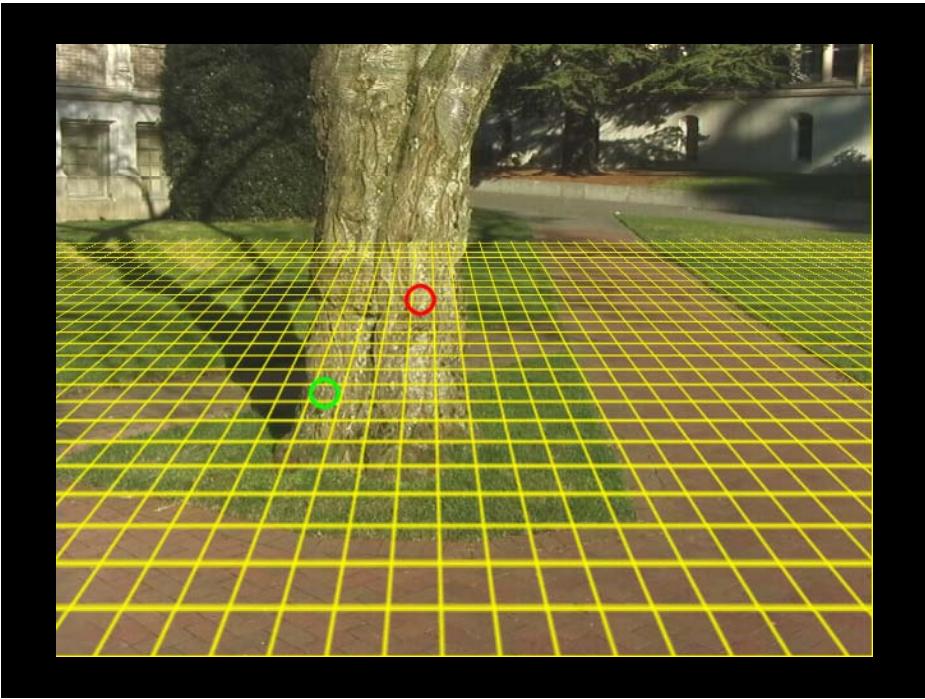


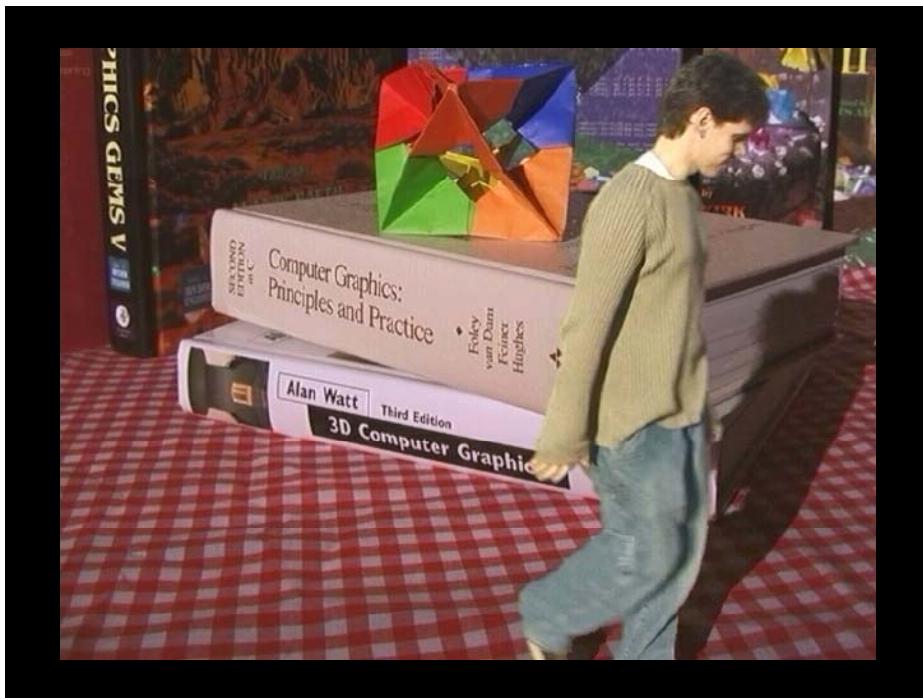
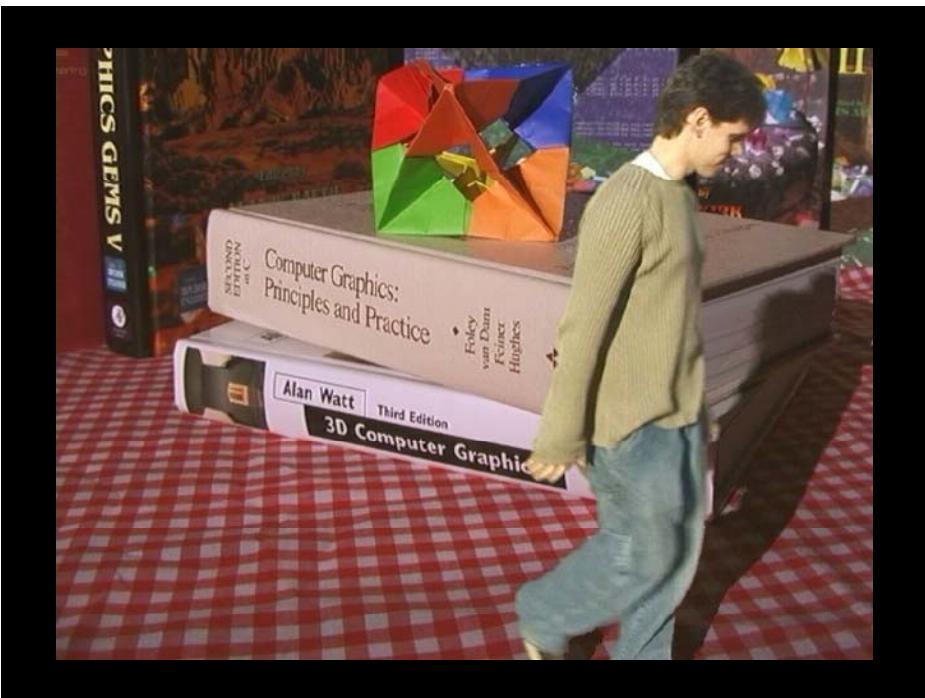
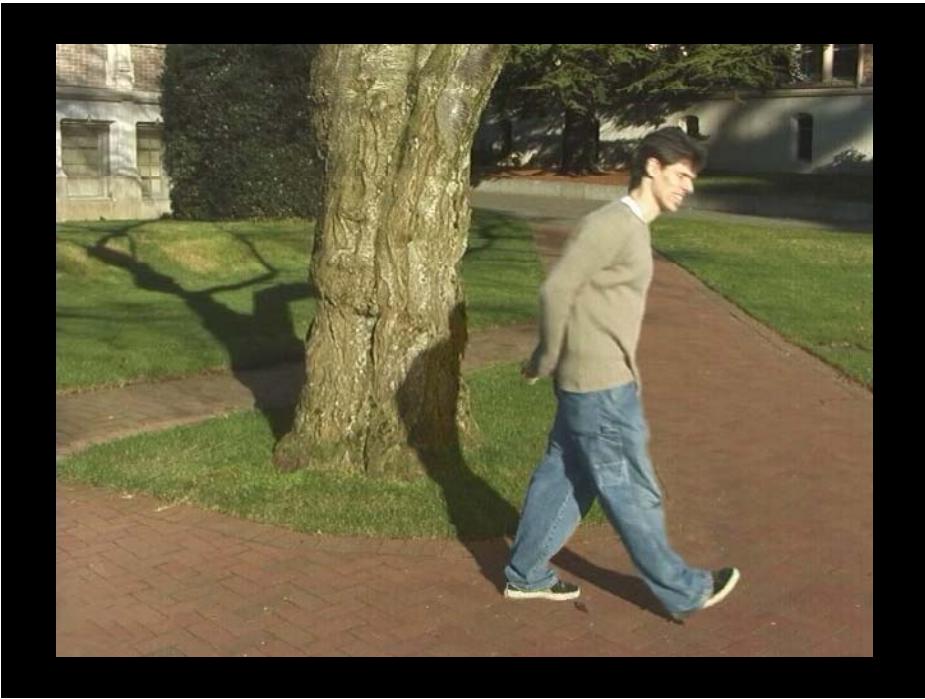












Environment matting

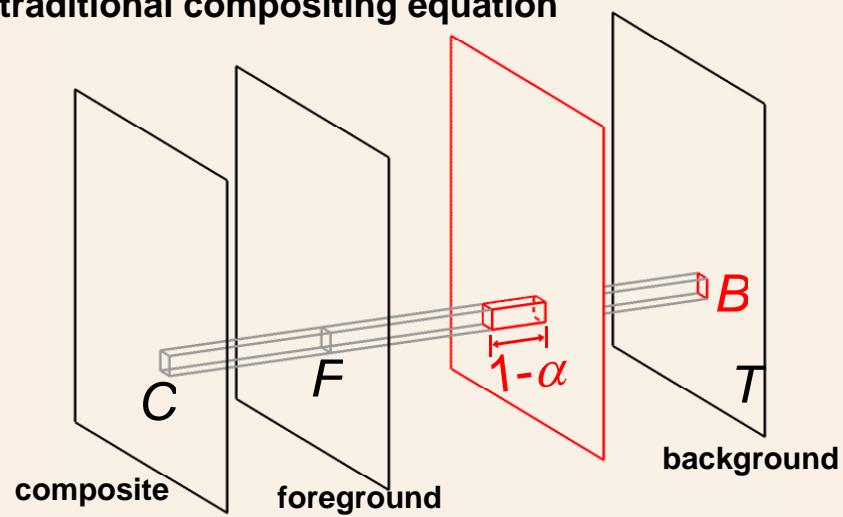
blue screen matting



photograph

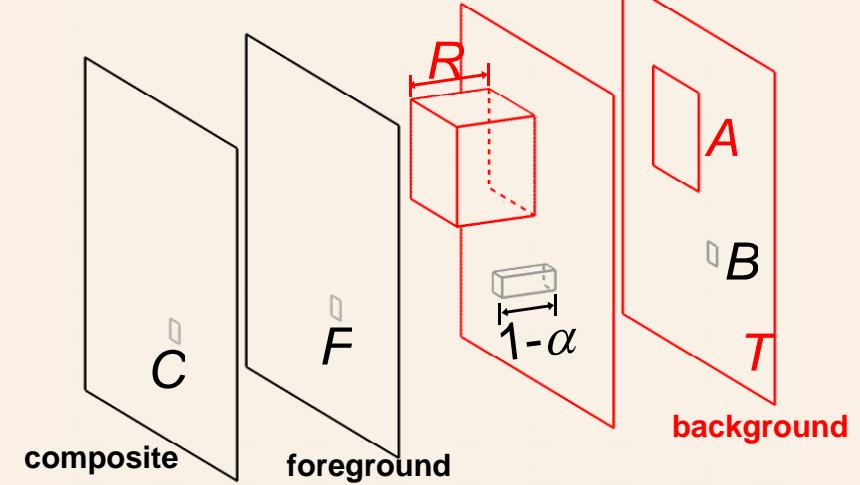


traditional compositing equation



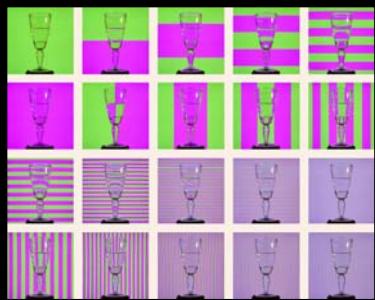
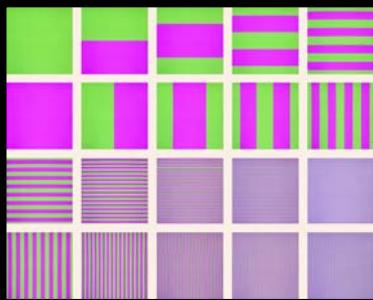
$$C = F + (1-\alpha)B$$

environment compositing equation [Zongker'99]



$$C = F + (1-\alpha)B + R\mathcal{M}(T, A)$$

$O(k)$ images



Environment matting [Zongker'99]

Zongker et al.



photograph



Problem: color dispersion

Zongker et al.



photograph



Problem: glossy surface

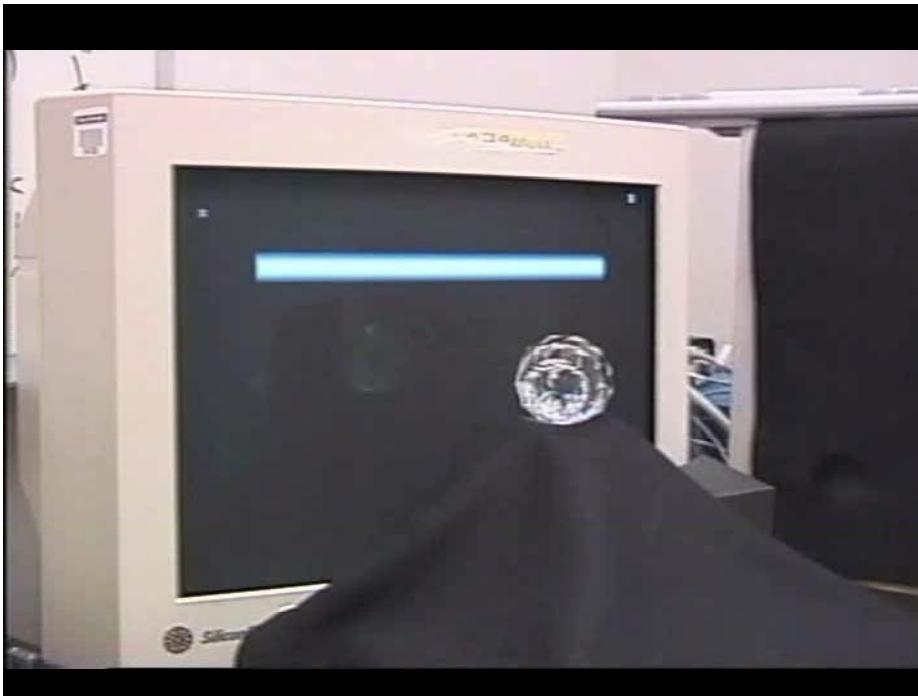
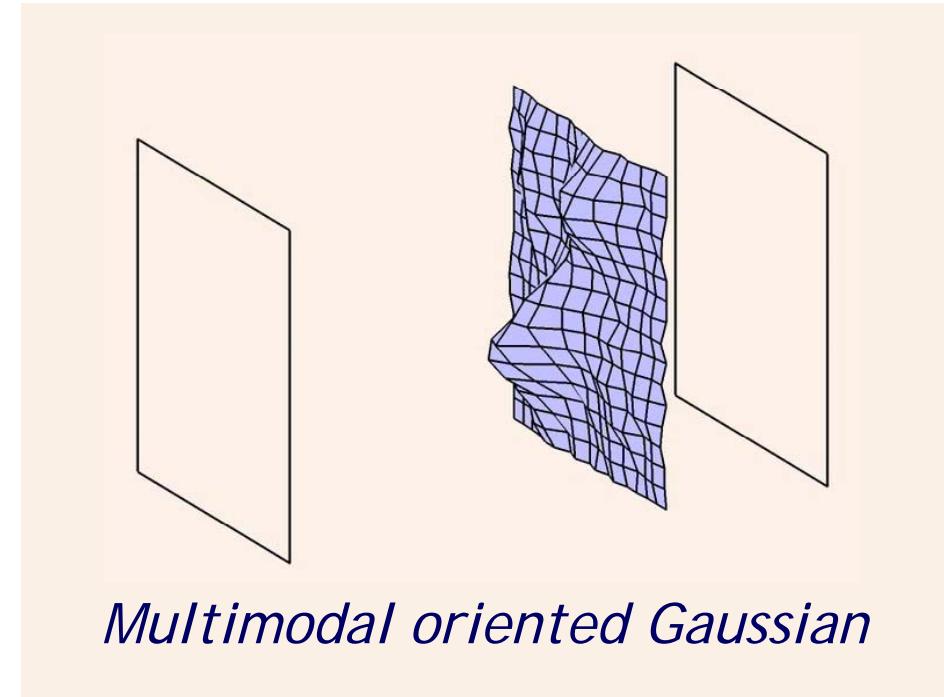
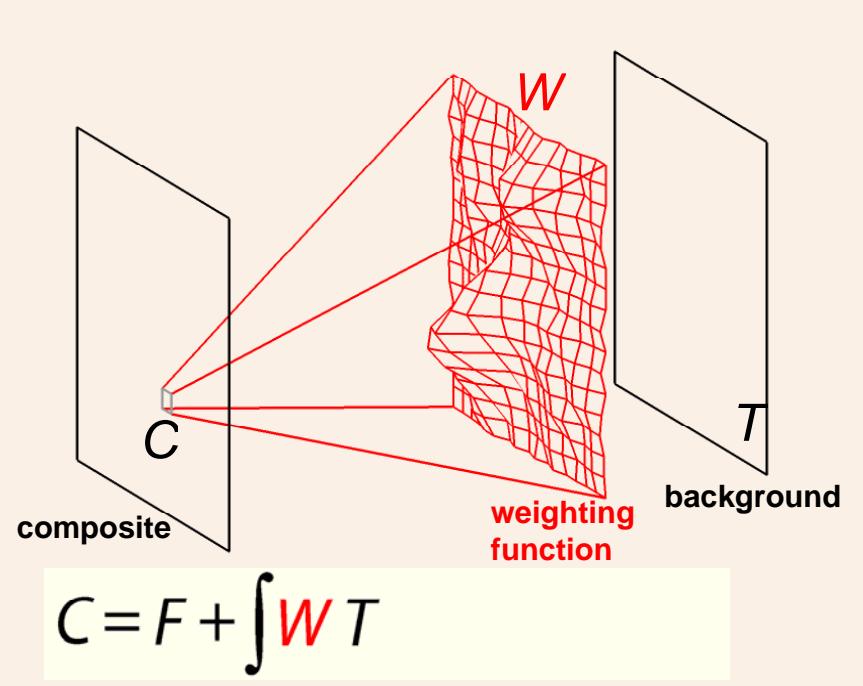
Zongker et al.



photograph

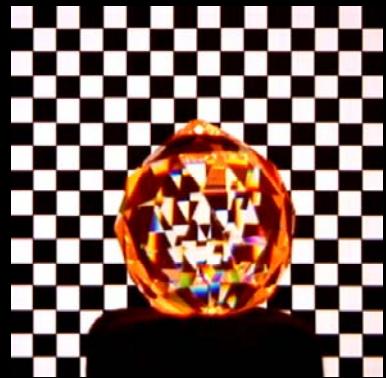
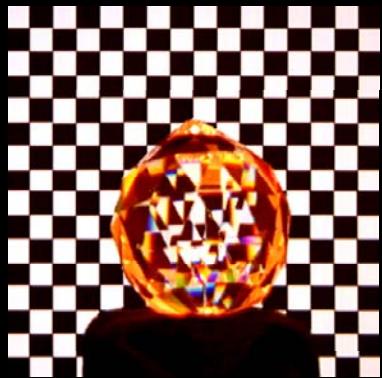


Problem: multiple mappings



high accuracy
algorithm

photograph



Problem: color dispersion

high accuracy
algorithm

photograph



Glossy surface

with
orientation

photograph



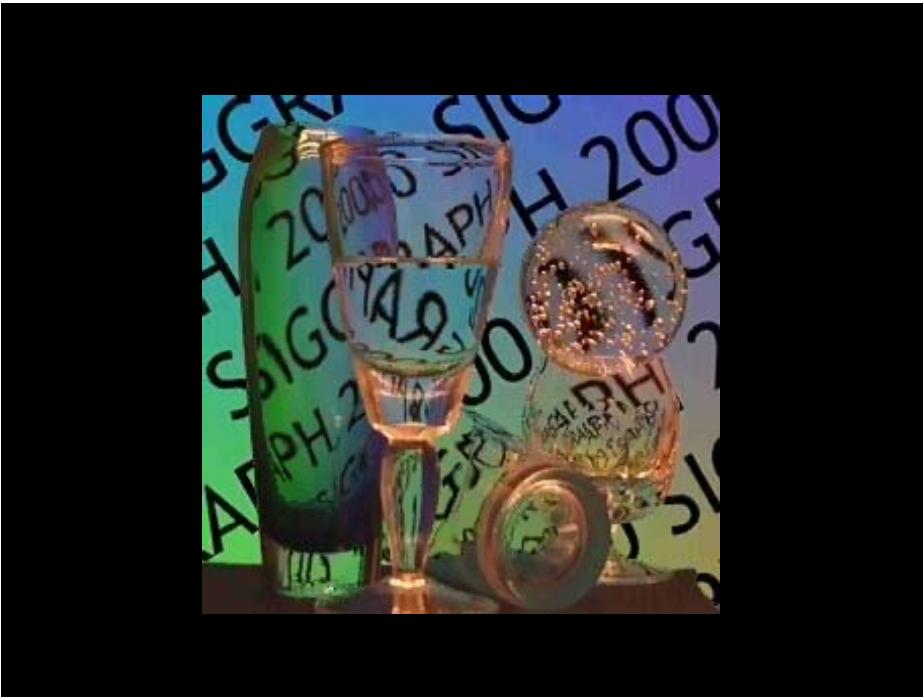
Oriented Gaussian

high accuracy
algorithm

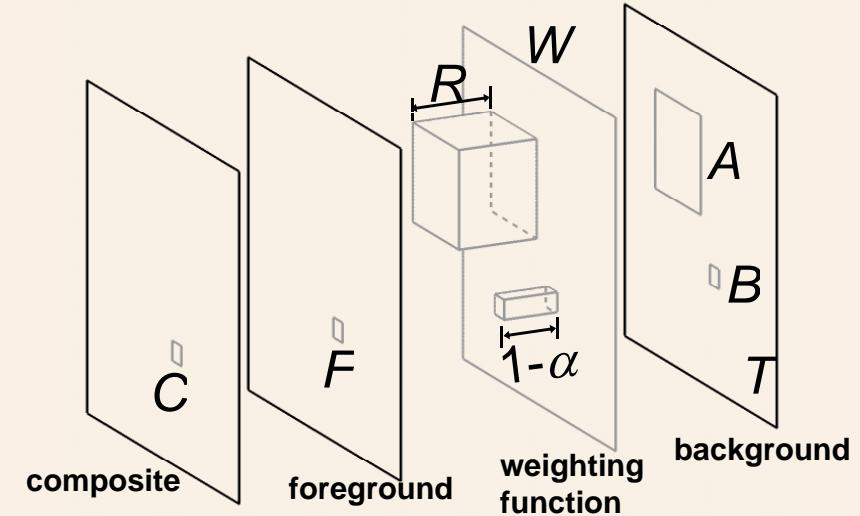
photograph



Problem: multiple mappings



$$C = F + (1-\alpha)B + R\mathcal{M}(T, A)$$



$$C = F + (1-\alpha)B + R\mathcal{M}(T, A)$$

3 3 1 3 4

3 observations
11 variables

- A, R
- α
- F

$$C = R\mathcal{M}(T, A)$$

3 3 4

3 observations
7 variables

- A, R
- α
- F

$$C = \rho M(T, A)$$

3 1 4

3 observations

5 variables

- $A, R \longrightarrow A, \rho$
- α colorless
- F

$$C = \rho T(c_x, -c_y)$$

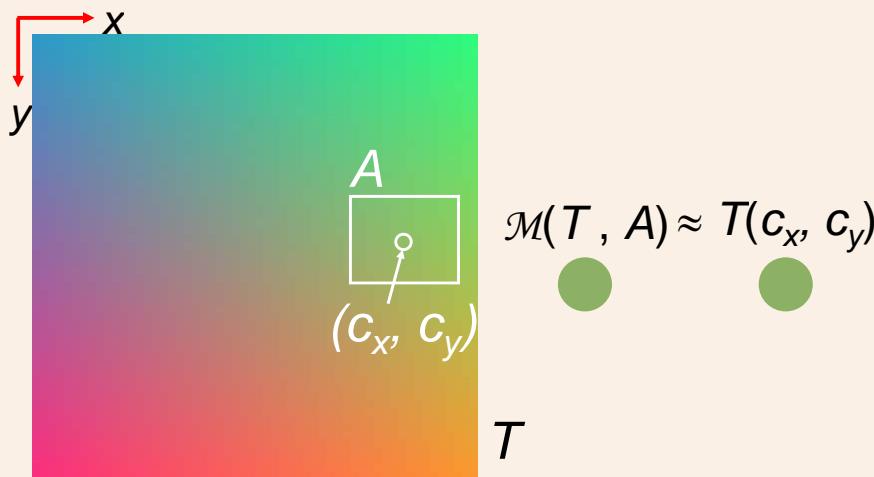
3 1 1 1

3 observations

3 variables

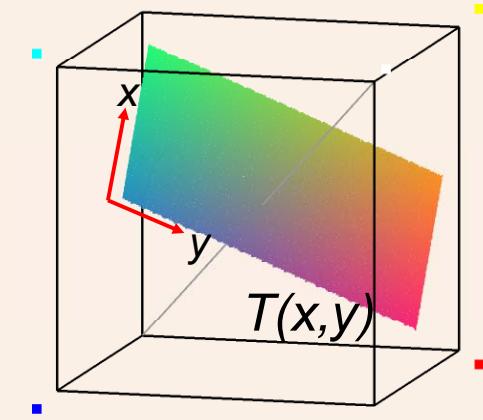
- $A, R \longrightarrow A, \rho \longrightarrow c_x, c_y, \rho$
- α colorless
- F specularly refractive

Stimulus function

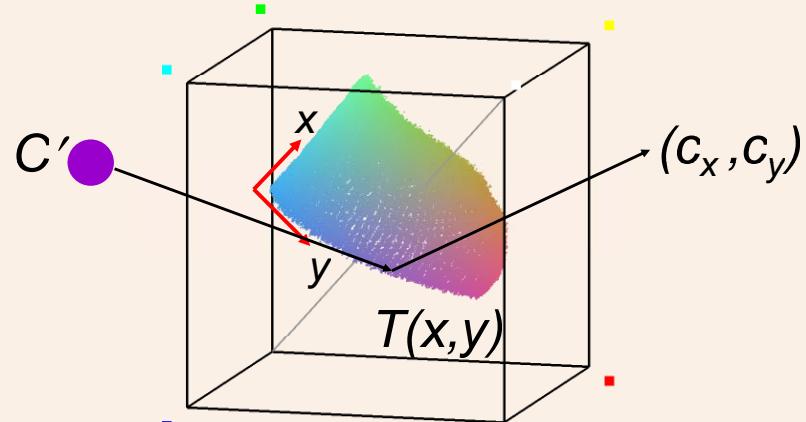


$$M(T, A) \approx T(c_x, c_y)$$

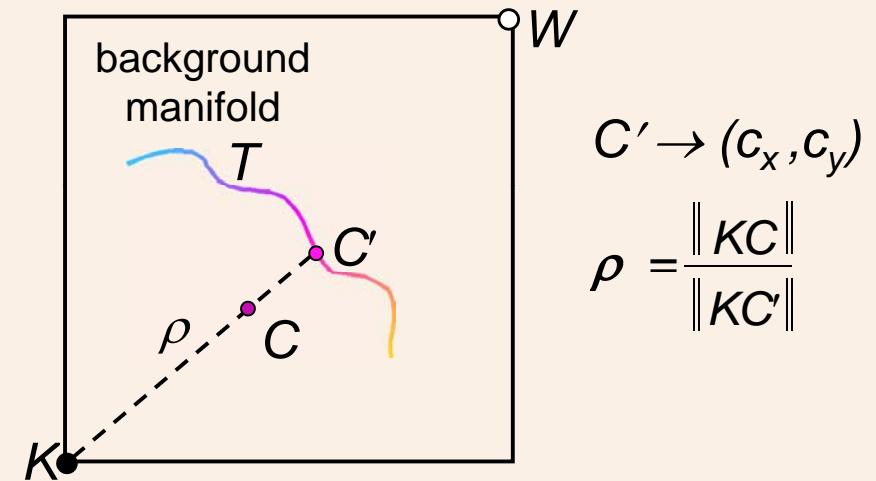
Ideal plane in RGB cube



Calibrated manifold in RGB cube



Estimate c_x, c_y and ρ



Problem: noisy matte



Edge-preserving filtering



without filtering

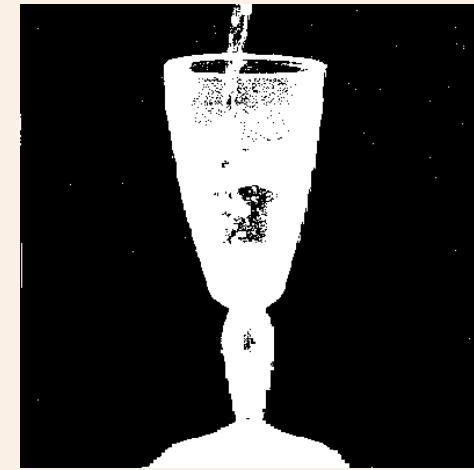


with filtering

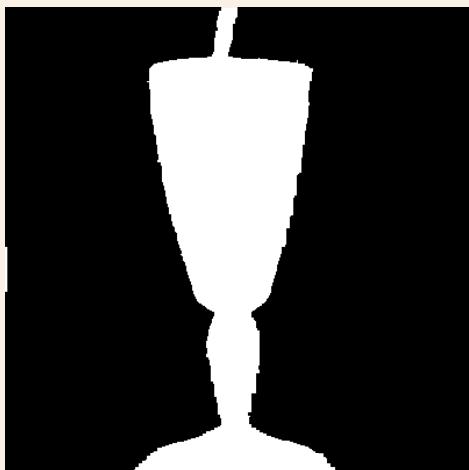
Input image



Difference thresholding



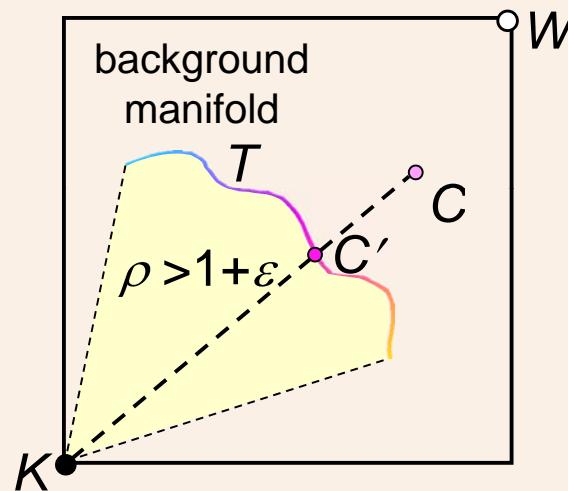
Morphological operation



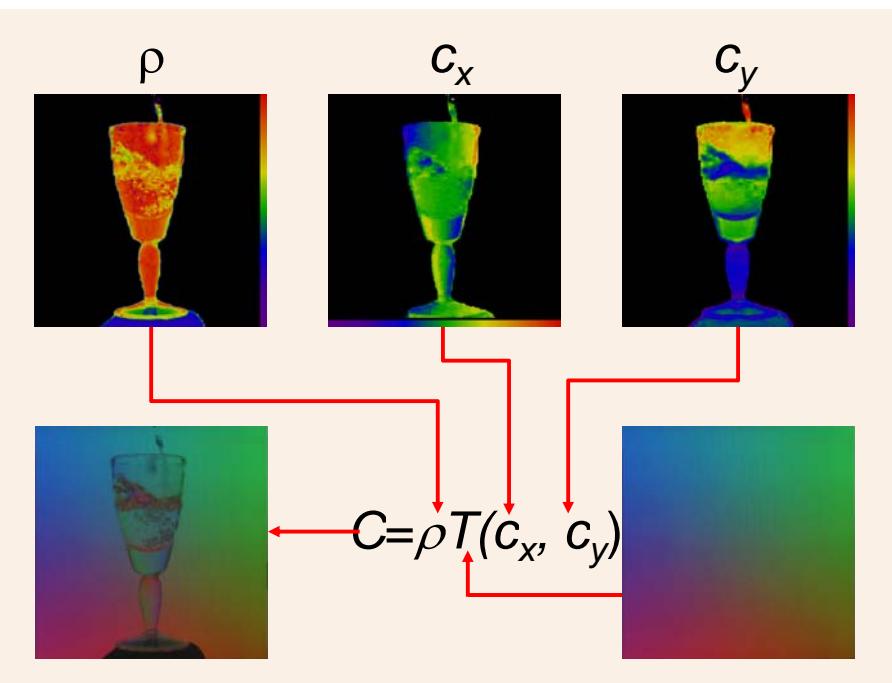
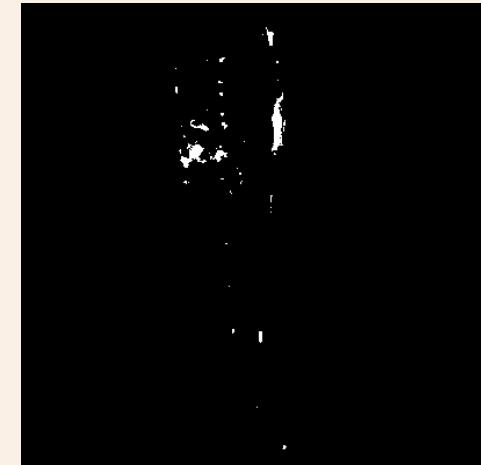
Feathering



Heuristics for specular highlights



Heuristics for specular highlights



Heuristics for specular highlights



Composite with highlights



	compositing model	matting method
color blending		blue-screen Bayesian
shadow		Shadow matting
refraction reflection		High-accuracy env. matting