Matting and Compositing

Digital Visual Effects, Spring 2009
Yung-Yu Chuang
2009/4/30

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.

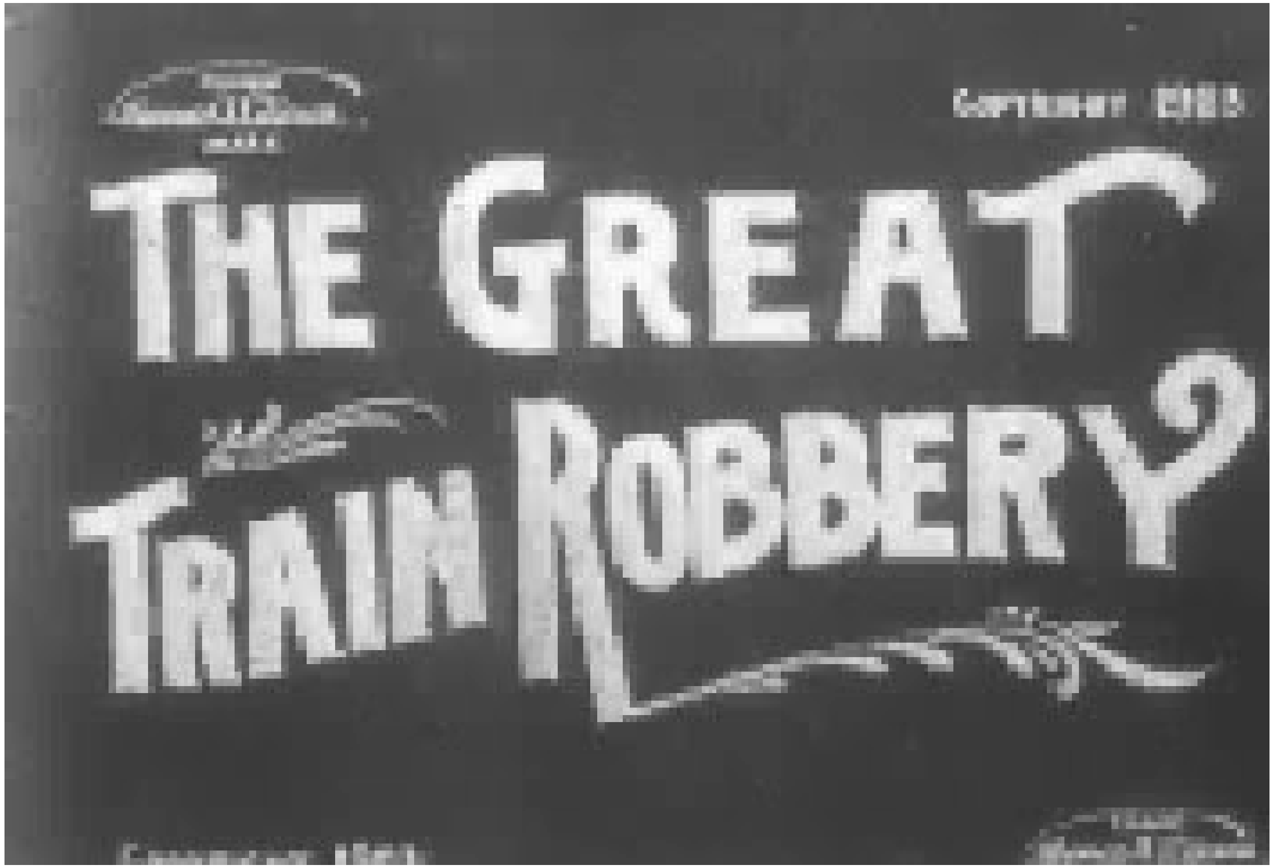
Photographic compositions

Lang Ching-shan

Use of mattes for compositing

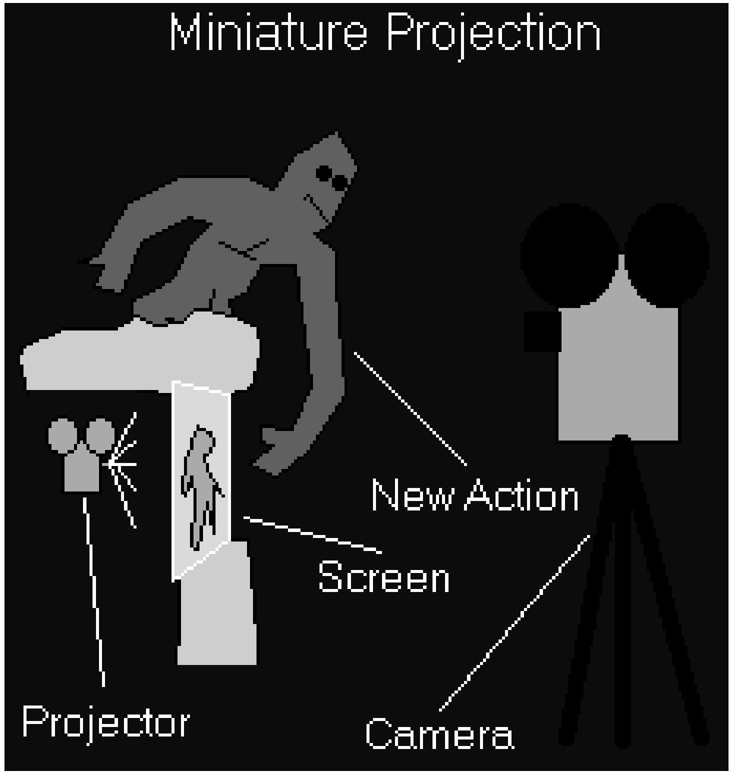
The Great Train Robbery (1903) matte shot

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 composting

King Kong (1933)

Optical compositing

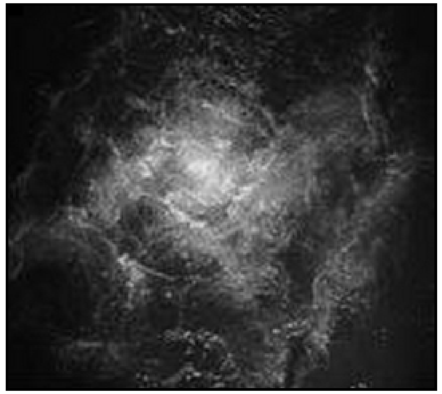
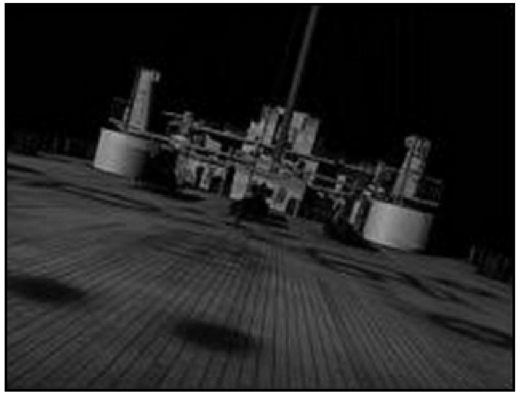
Jurassic Park III (2001)

Blue-screen matting,
digital composition,
digital matte painting

Smith Duff Catmull Porter

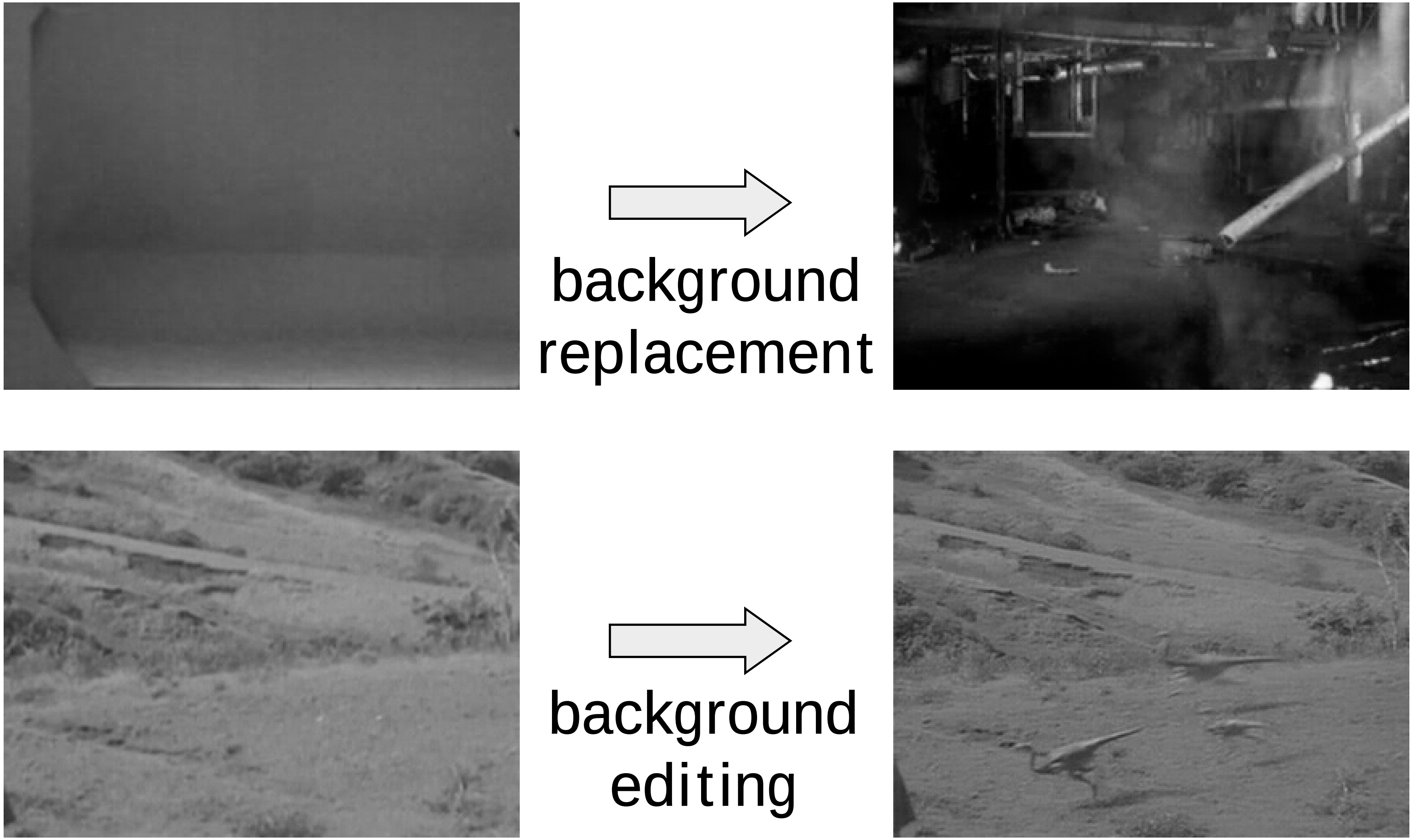
Oscar award, 1996



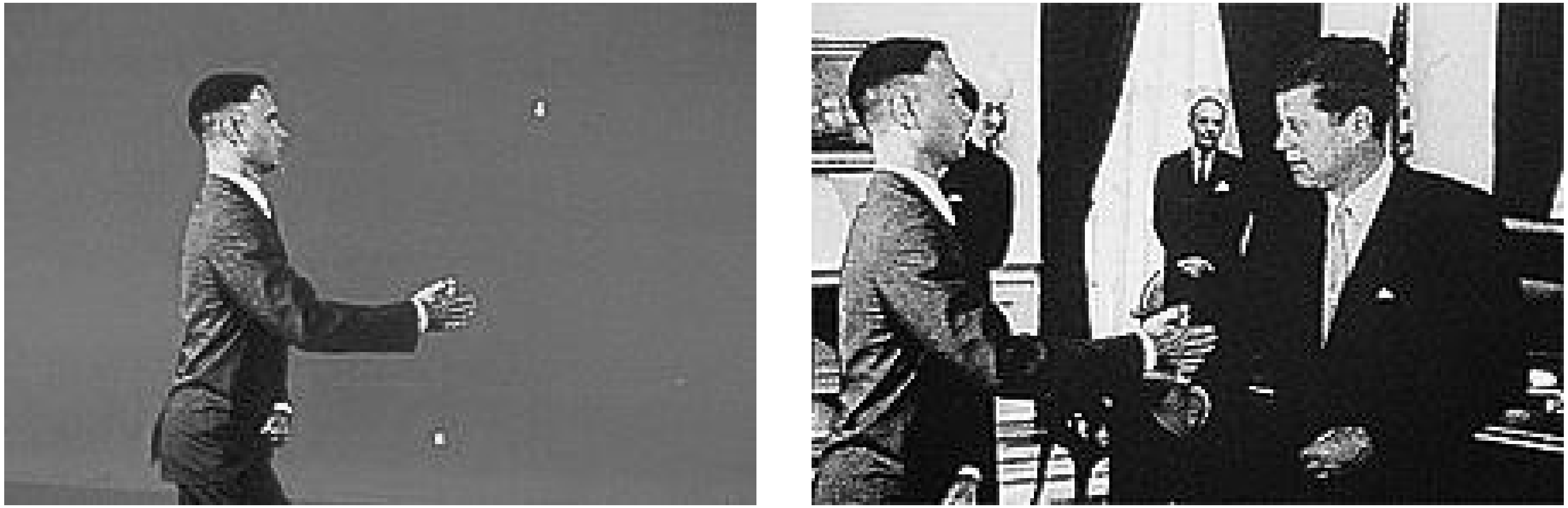
Titanic

Matting and Compositing



Matting and Compositing

Digital matting: bluescreen matting

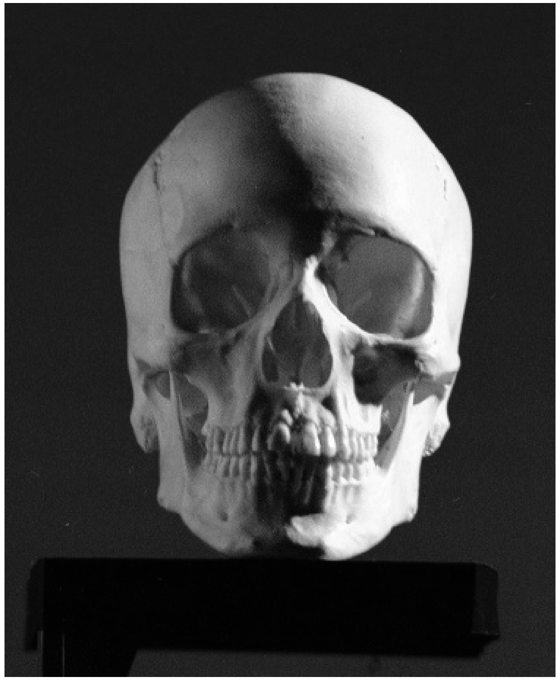


Forrest Gump (1994)

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

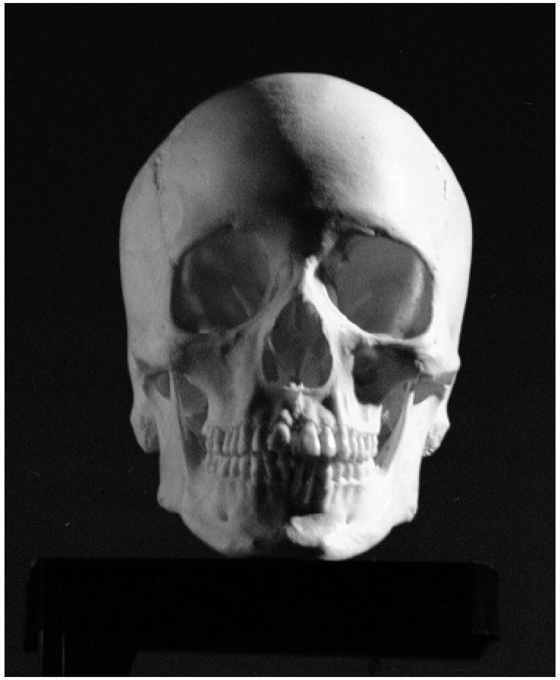
Color difference method (Ultimatte)

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



Blue-screen
photograph

F



Spill suppression
if B>G then B=G

$\bar{\alpha}$

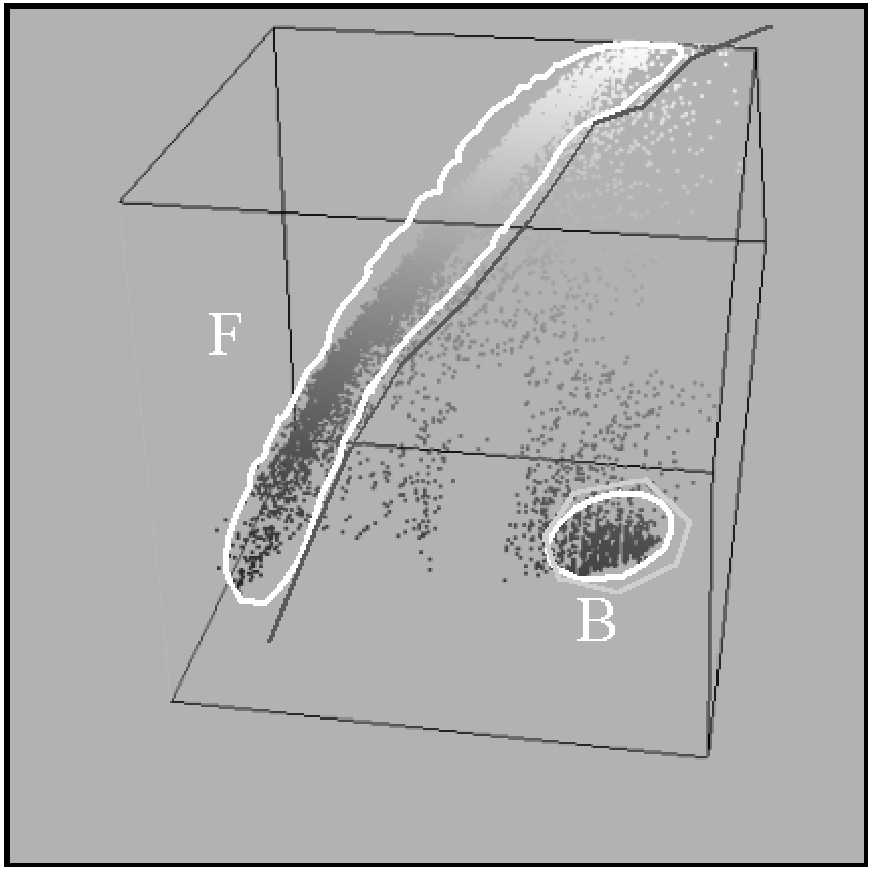
Matte creation
$\bar{\alpha}=B-\max(G,R)$

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

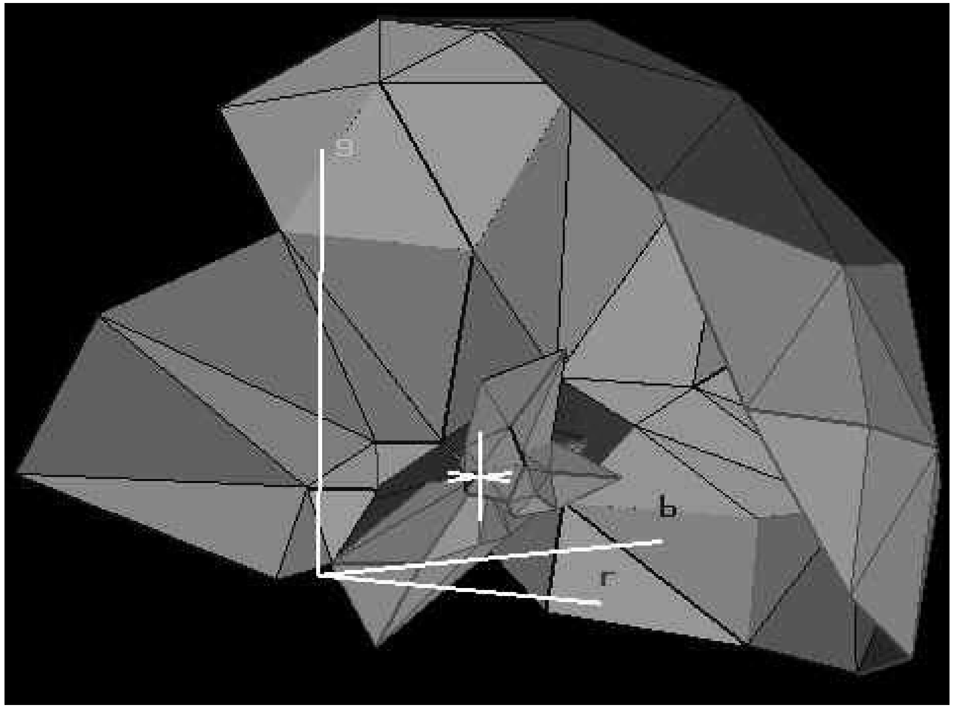
Problems with color difference

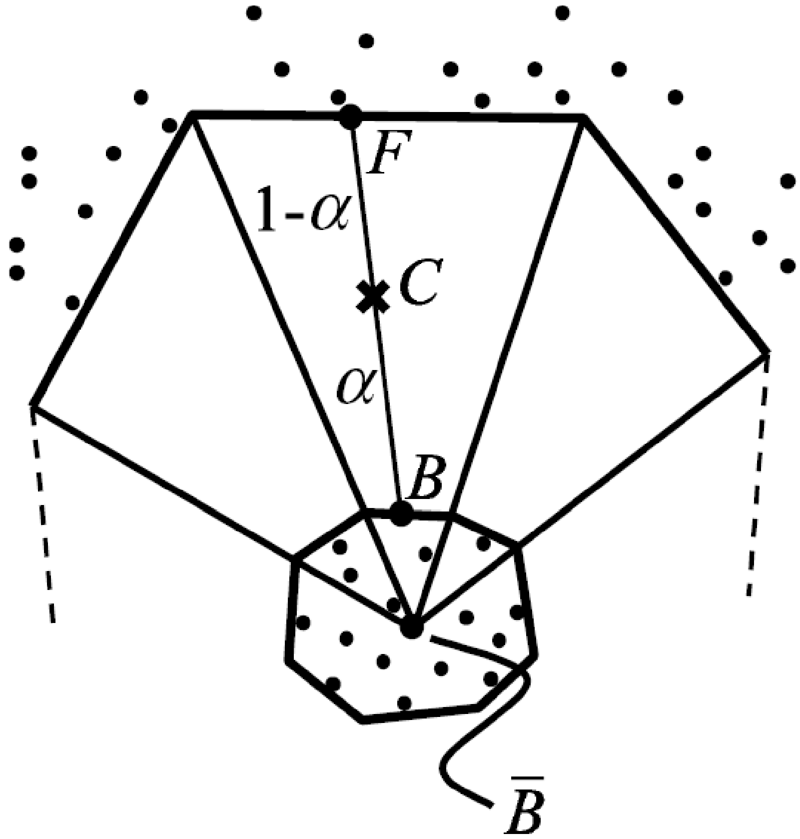
Background color is usually not perfect! (lighting, shadowing...)

Chroma-keying (Primatte)



Chroma-keying (Primatte)





demo

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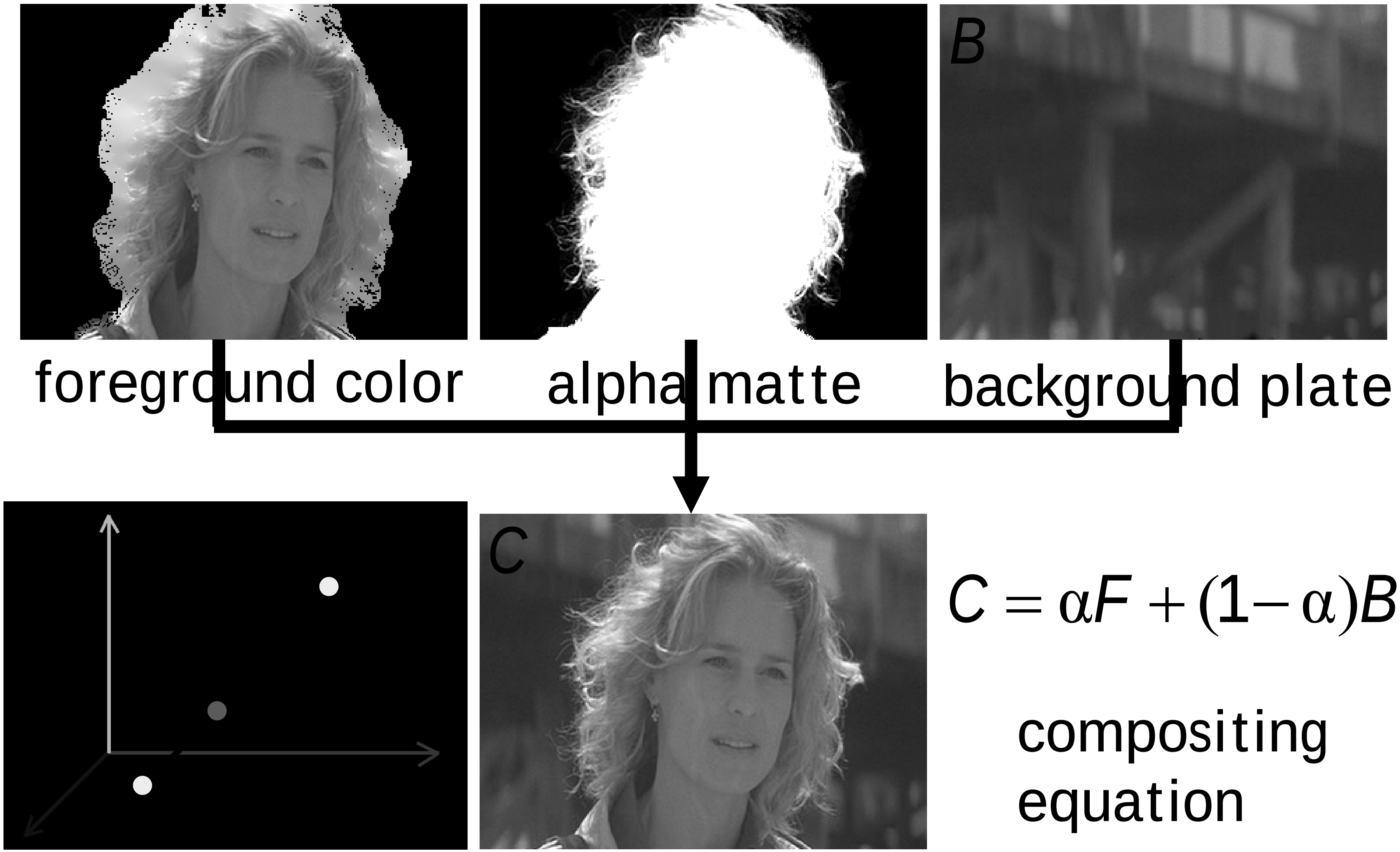
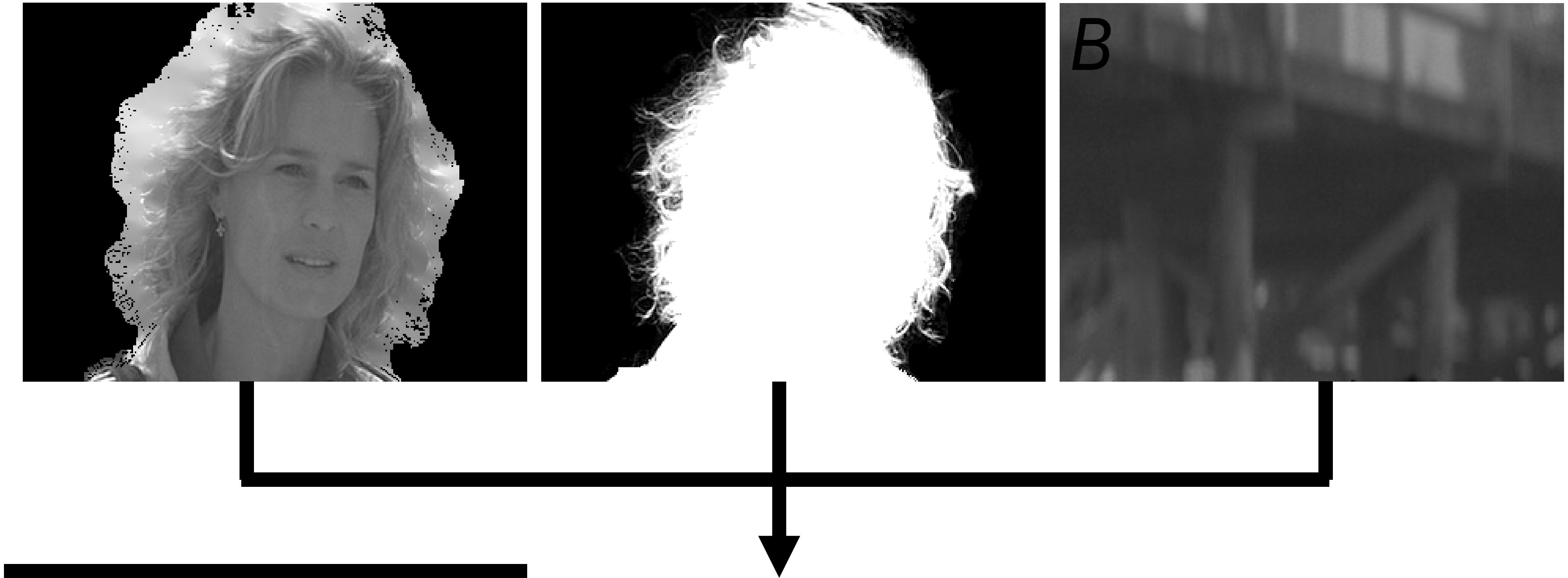
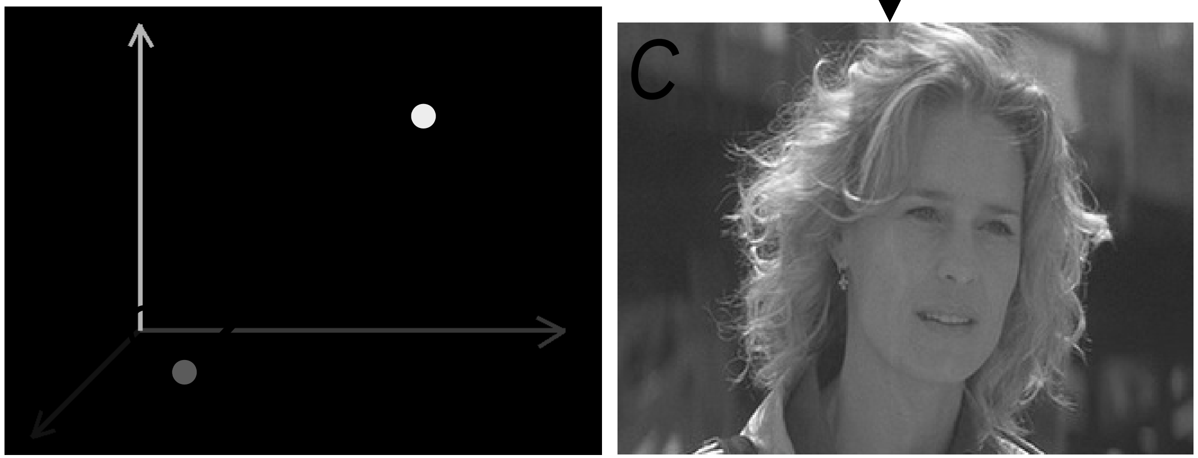


$$C = \alpha F + (1 - \alpha) B$$

compositing
equation

Compositing

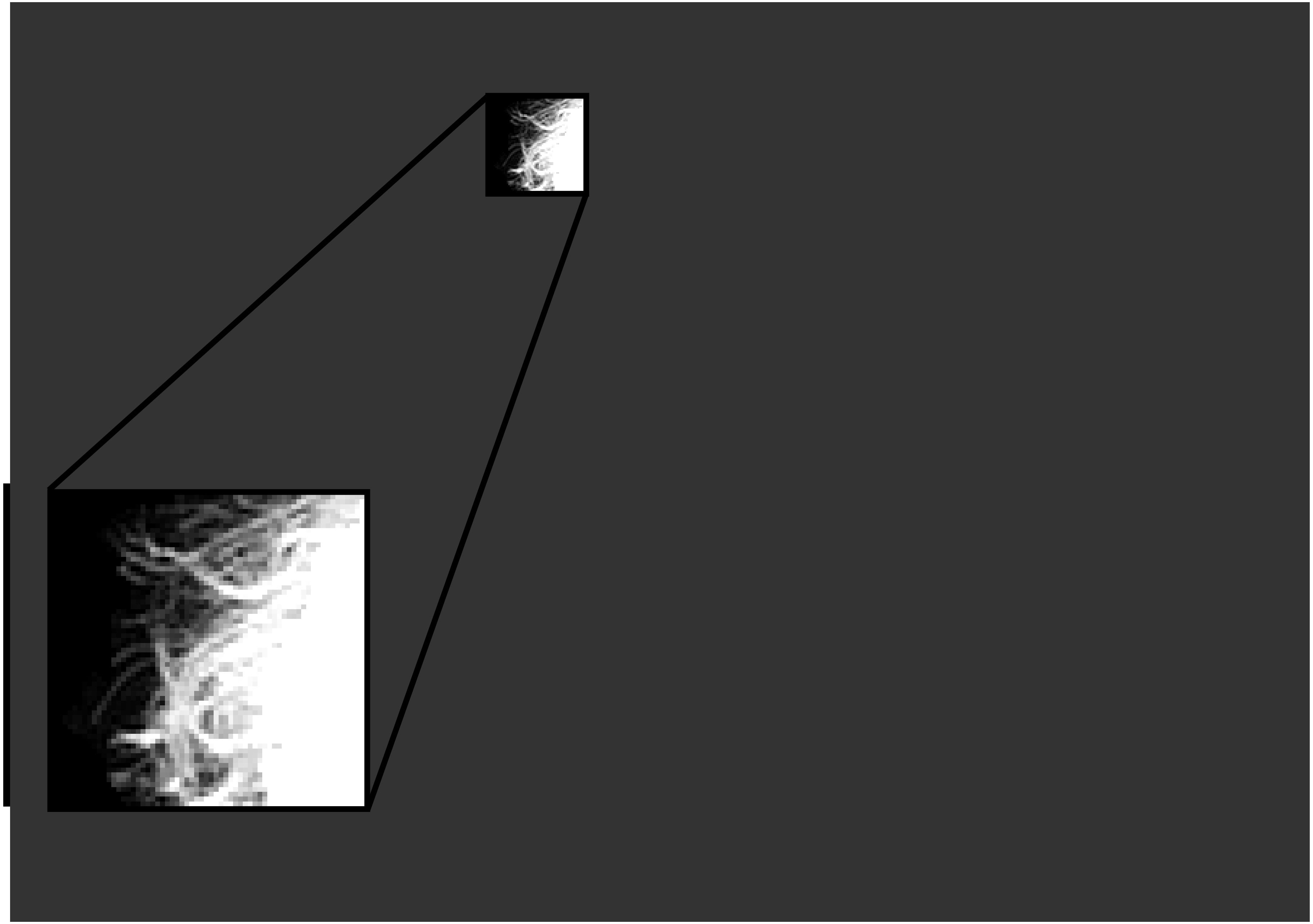


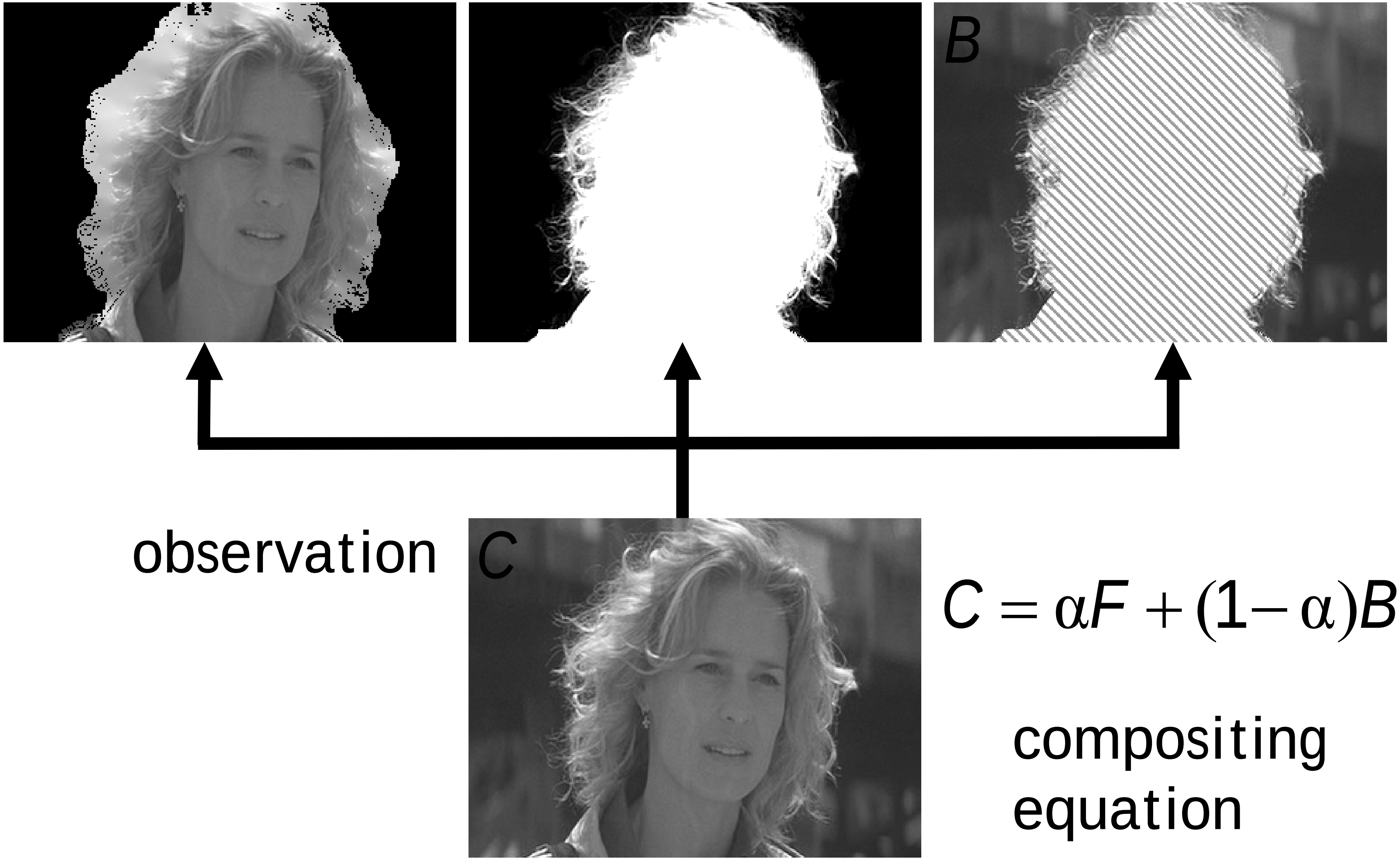


$$C = \alpha F + (1 - \alpha) B$$

compositing
equation

Compositing

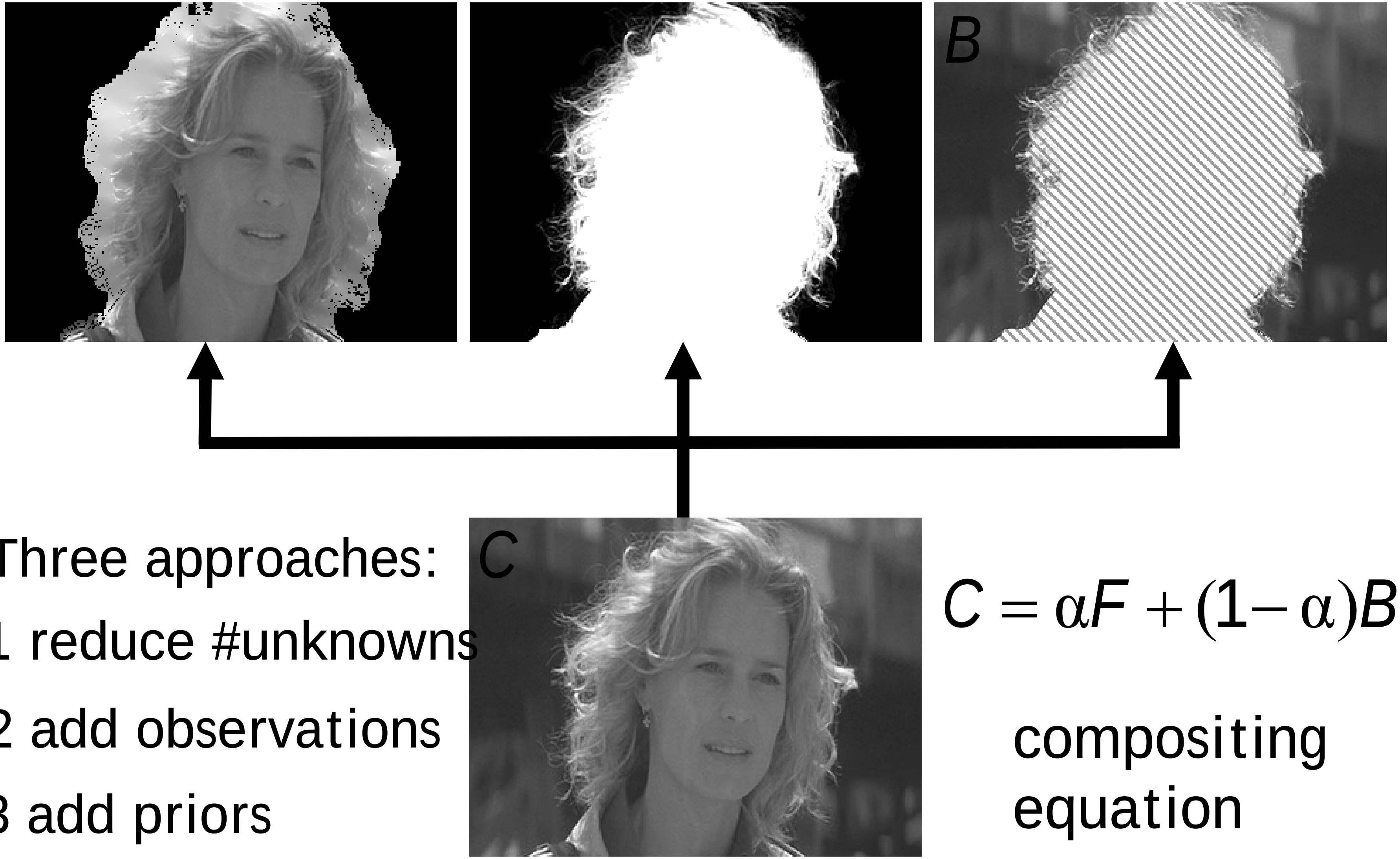




$$C = \alpha F + (1 - \alpha) B$$

compositing equation

Matting



Three approaches:

1 reduce #unknowns

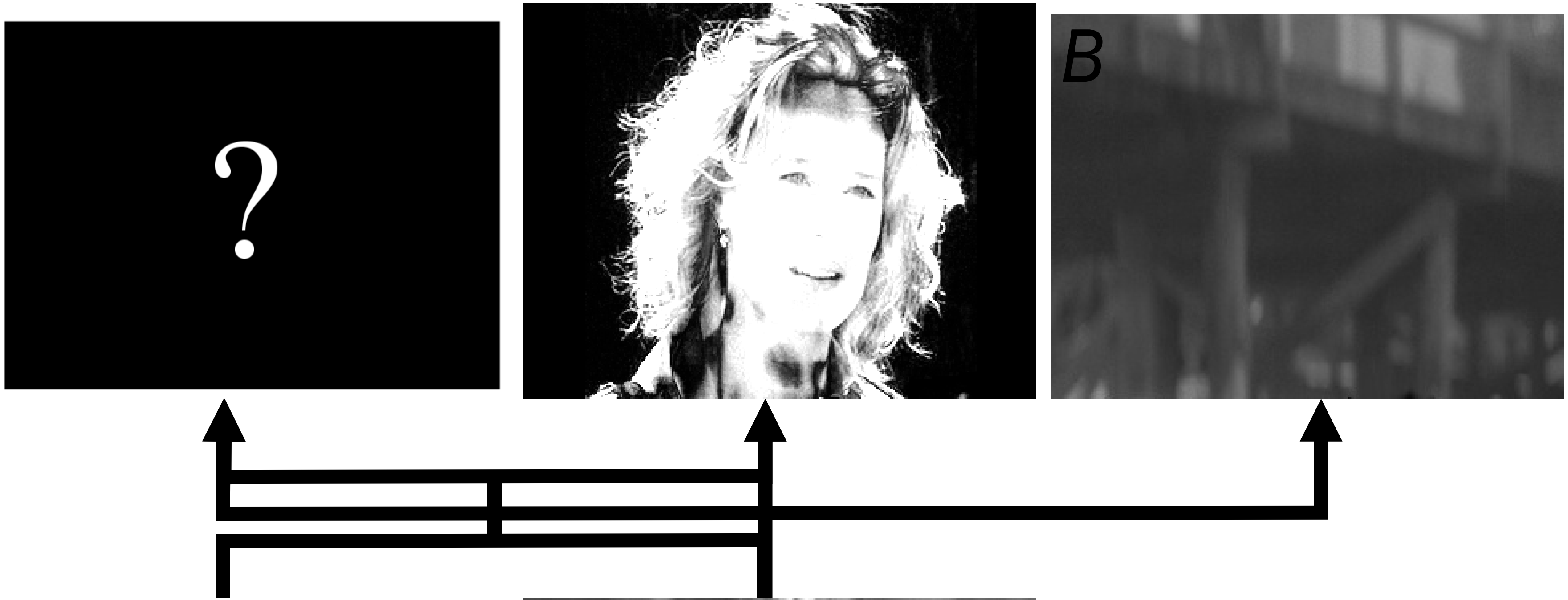
2 add observations

3 add priors

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

compositing equation

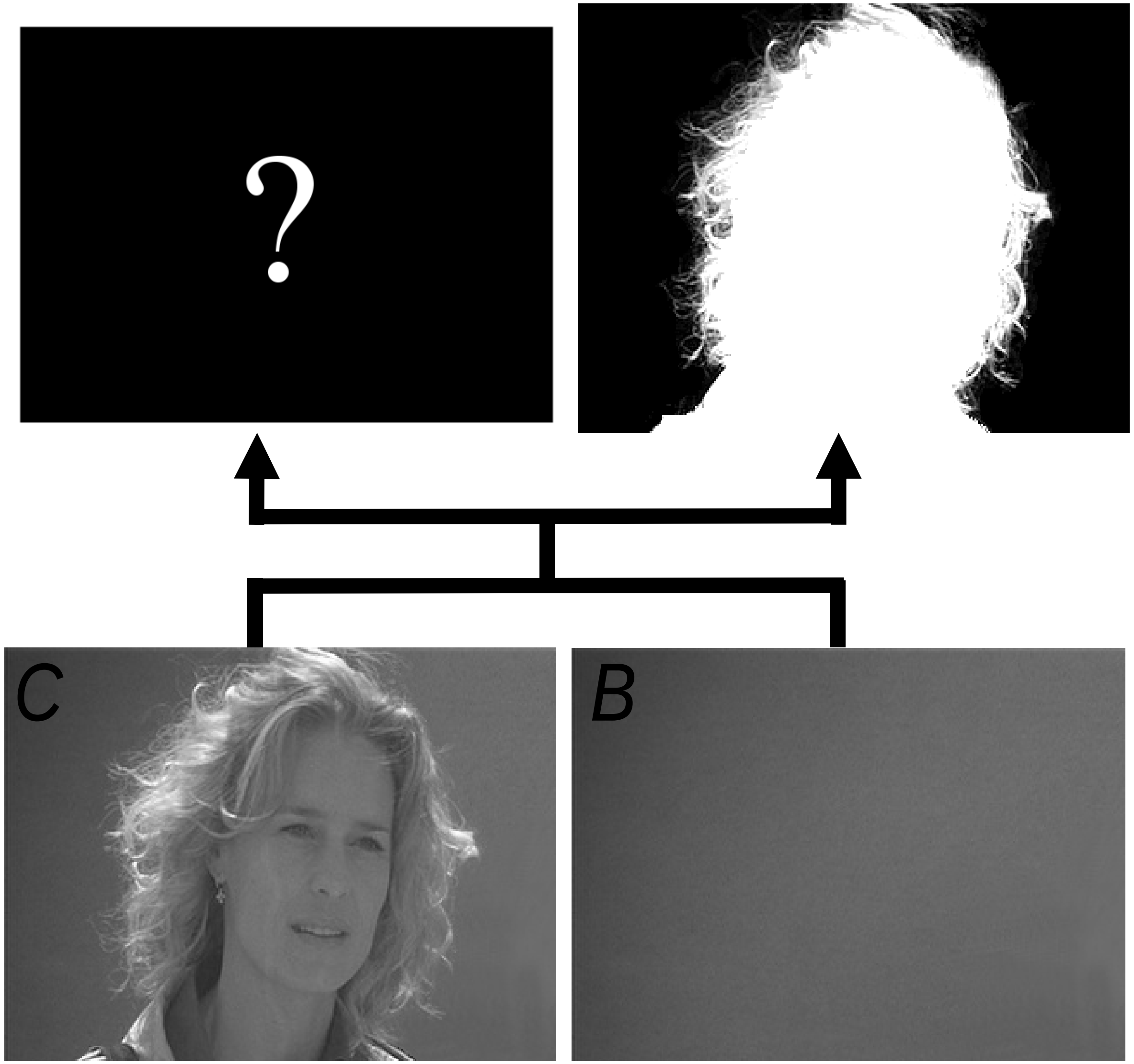
Matting



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

difference
matting

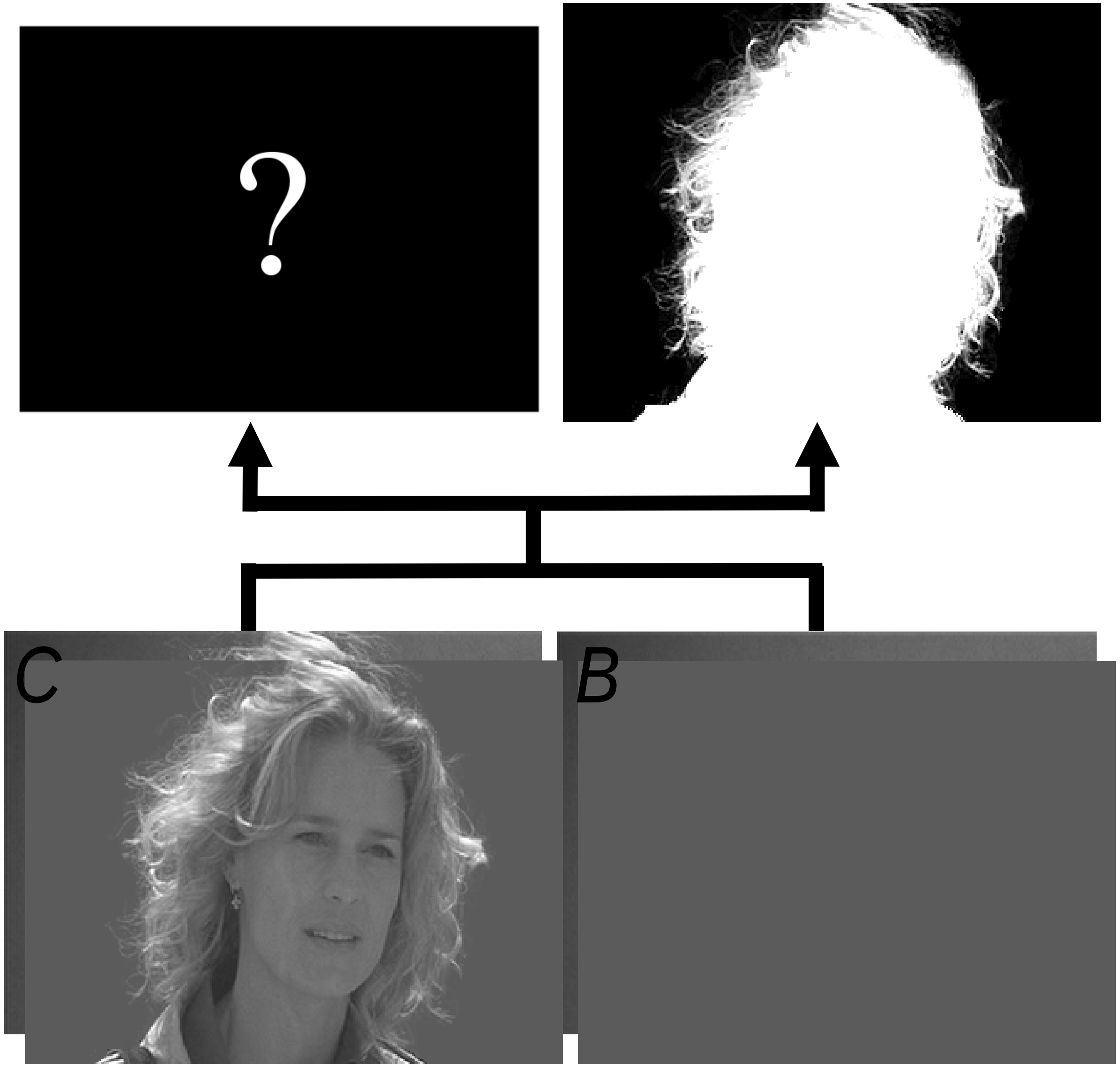
Matting (reduce #unknowns)



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

blue screen
matting

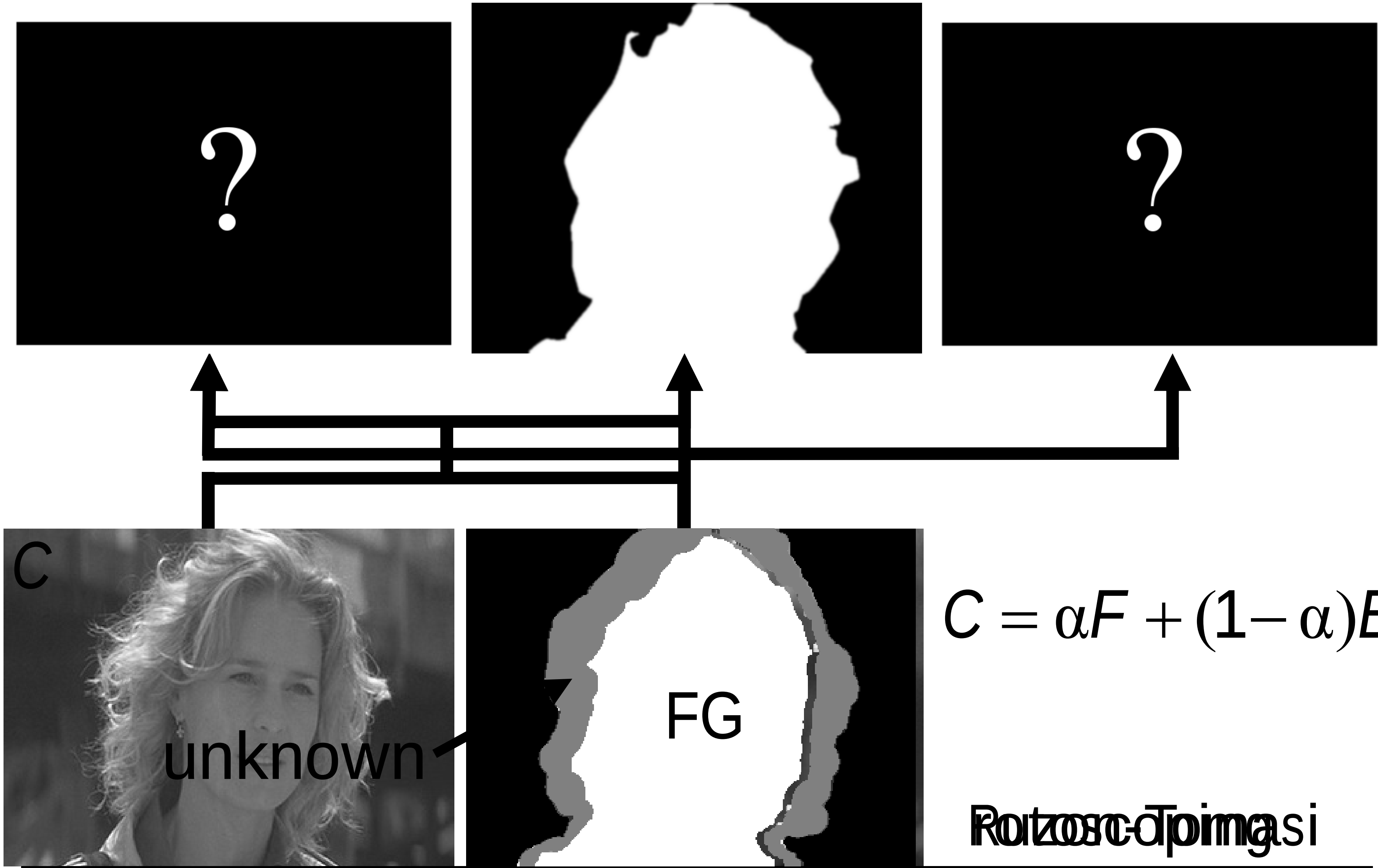
Matting (reduce #unknowns)



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

triangulation

Matting (add observations)



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

Ruzon-Tomasi

Matting (add priors)

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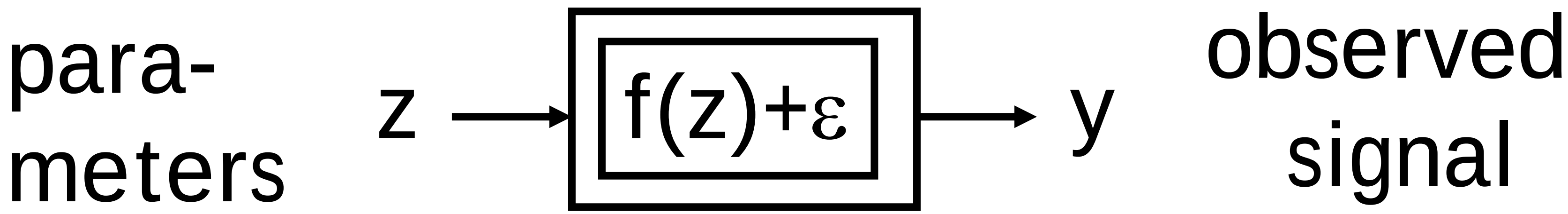


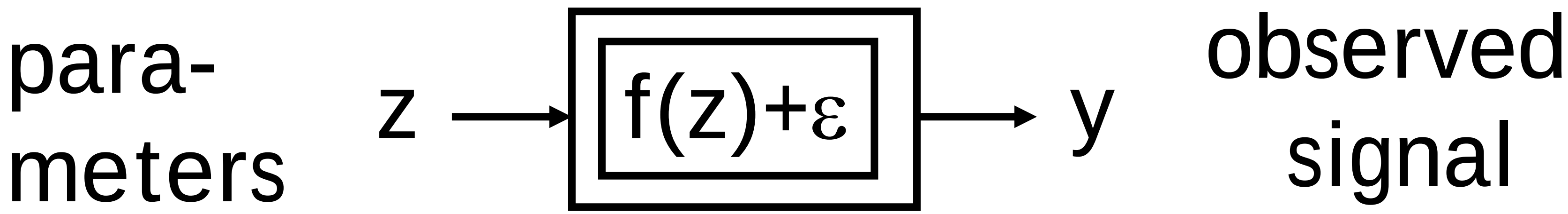
$$z^* = \max_z P(z \mid y)$$

$$= \max_z \frac{P(y \mid z)P(z)}{P(y)}$$

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

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

Bayesian framework



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

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

a-priori knowledge

Bayesian framework

posterior probability

likelihood

priors

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

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

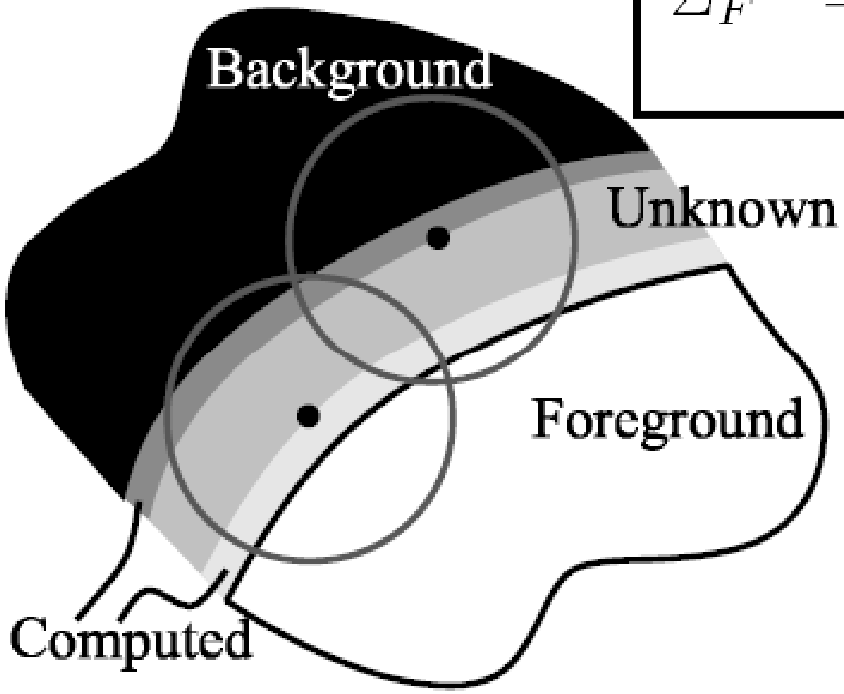
[redacted]

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

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

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

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

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

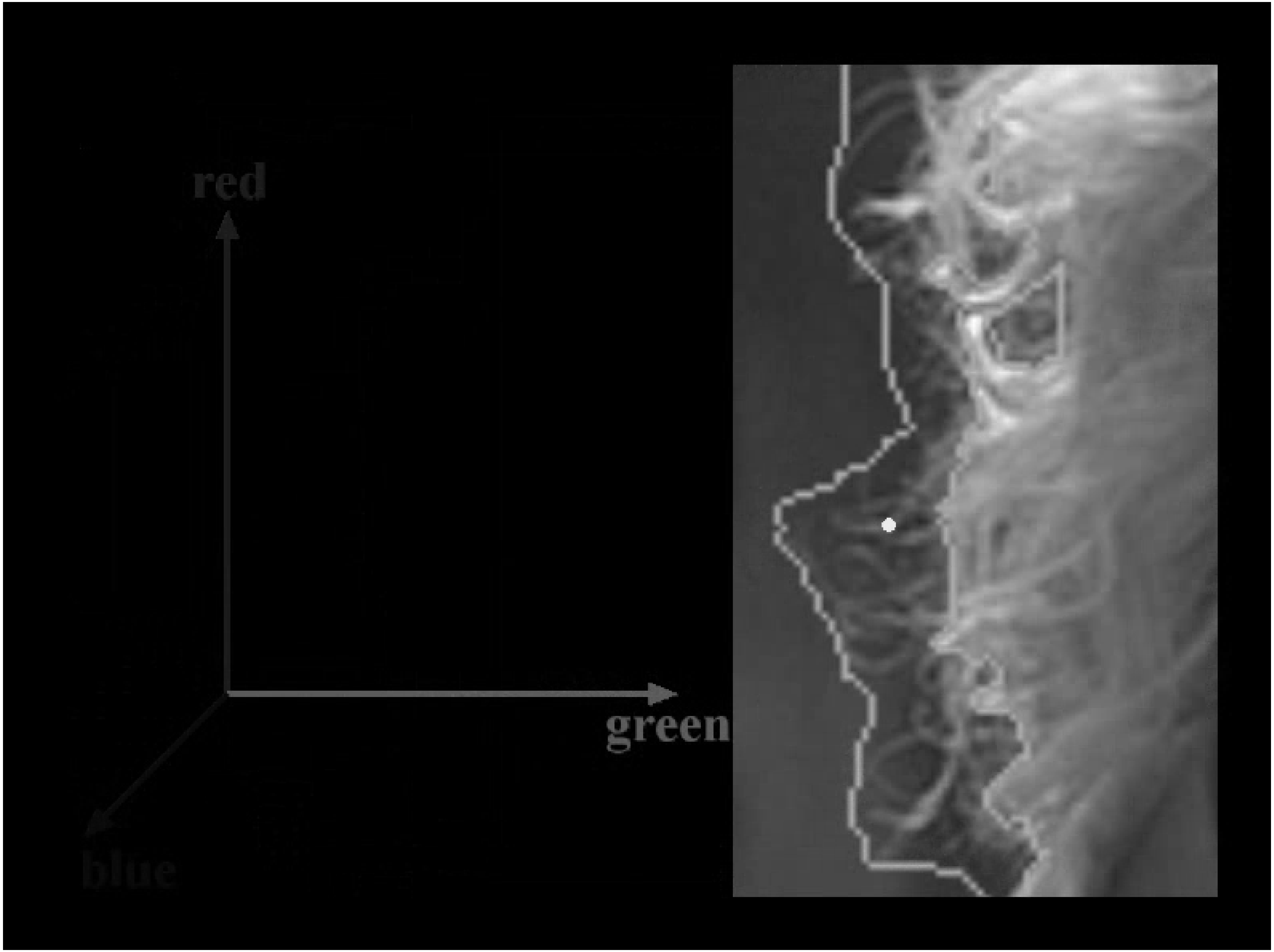
Bayesian image matting

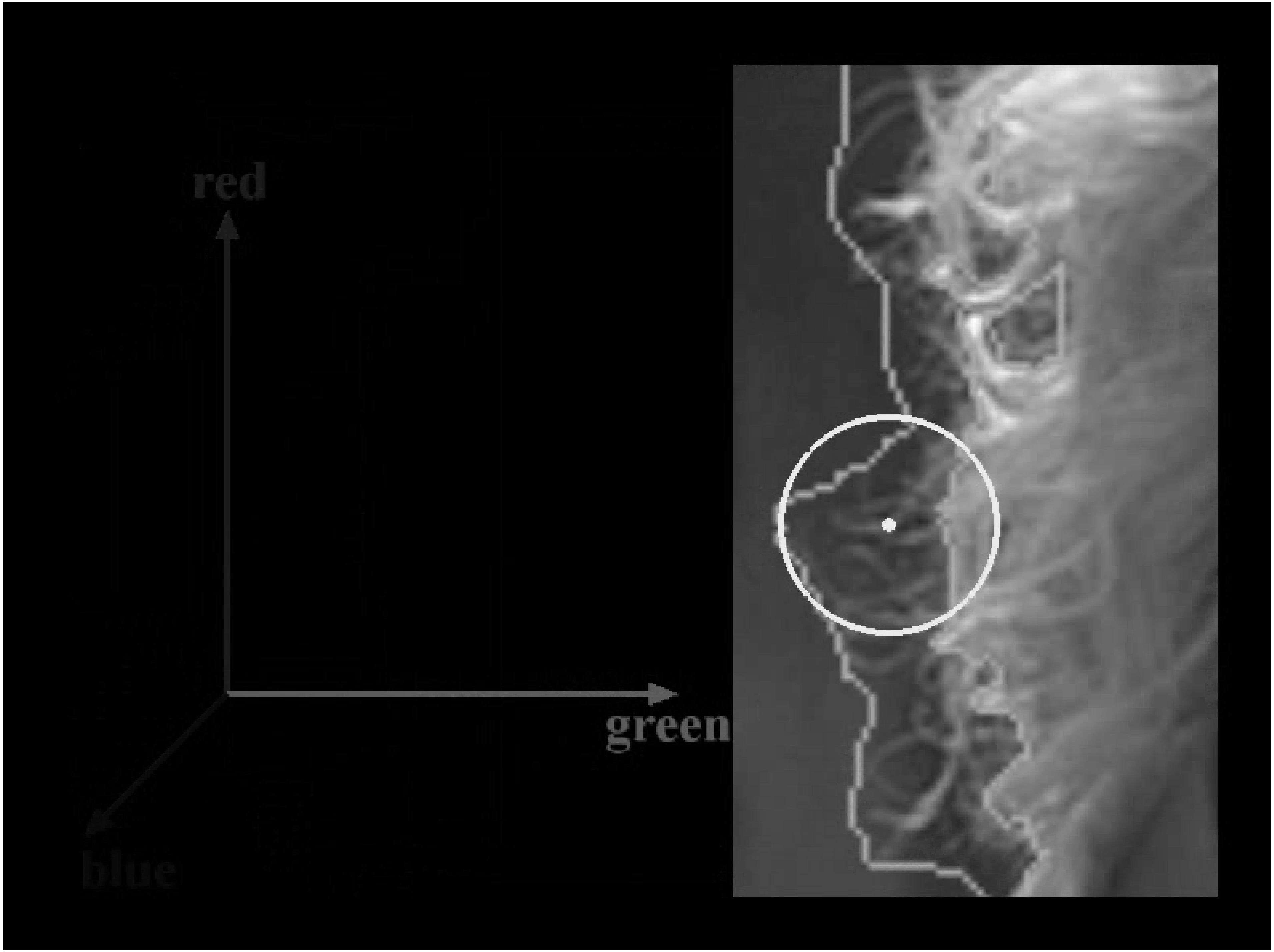
Bayesian image matting

Bayesian image matting

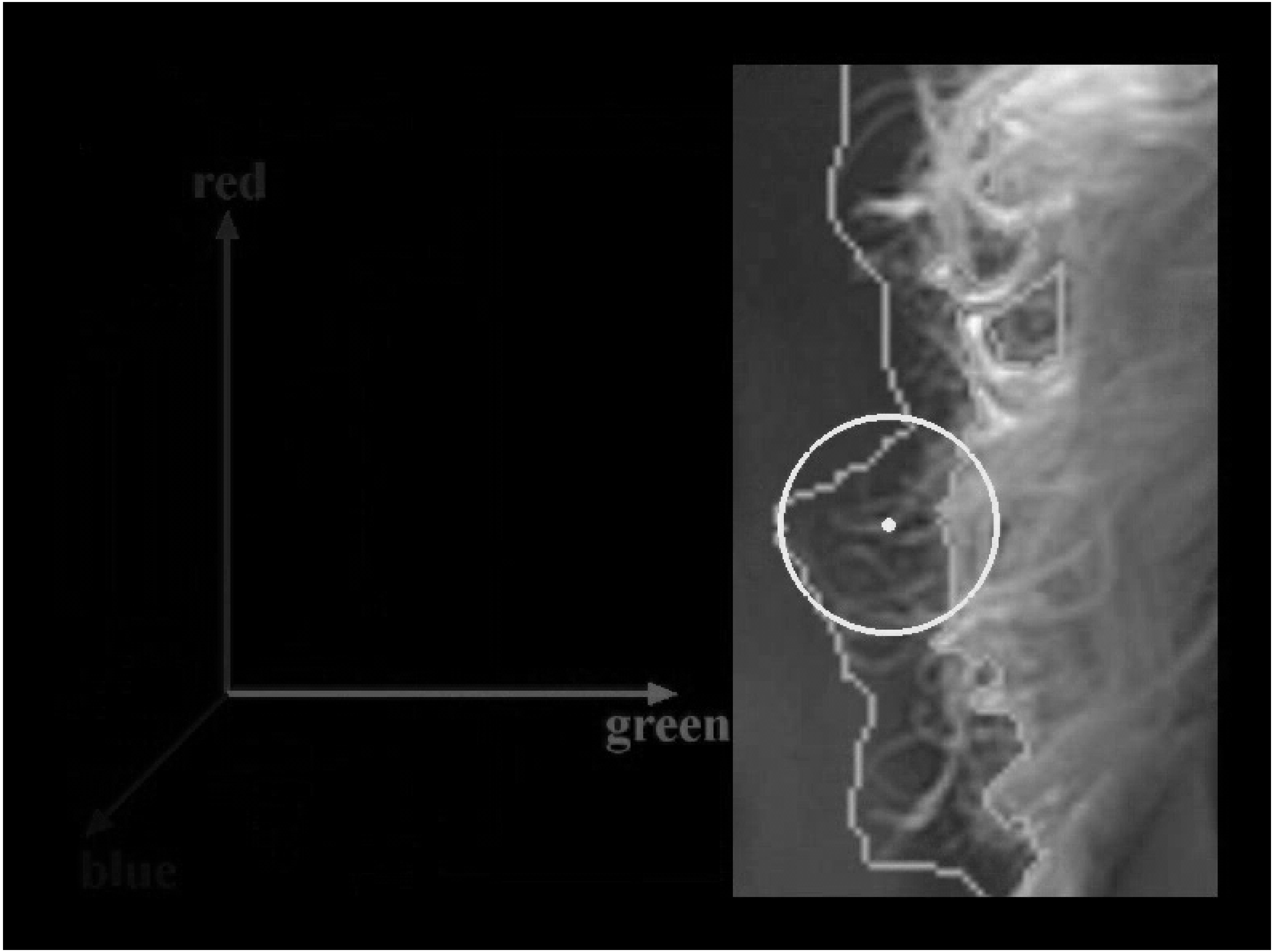
Bayesian image matting

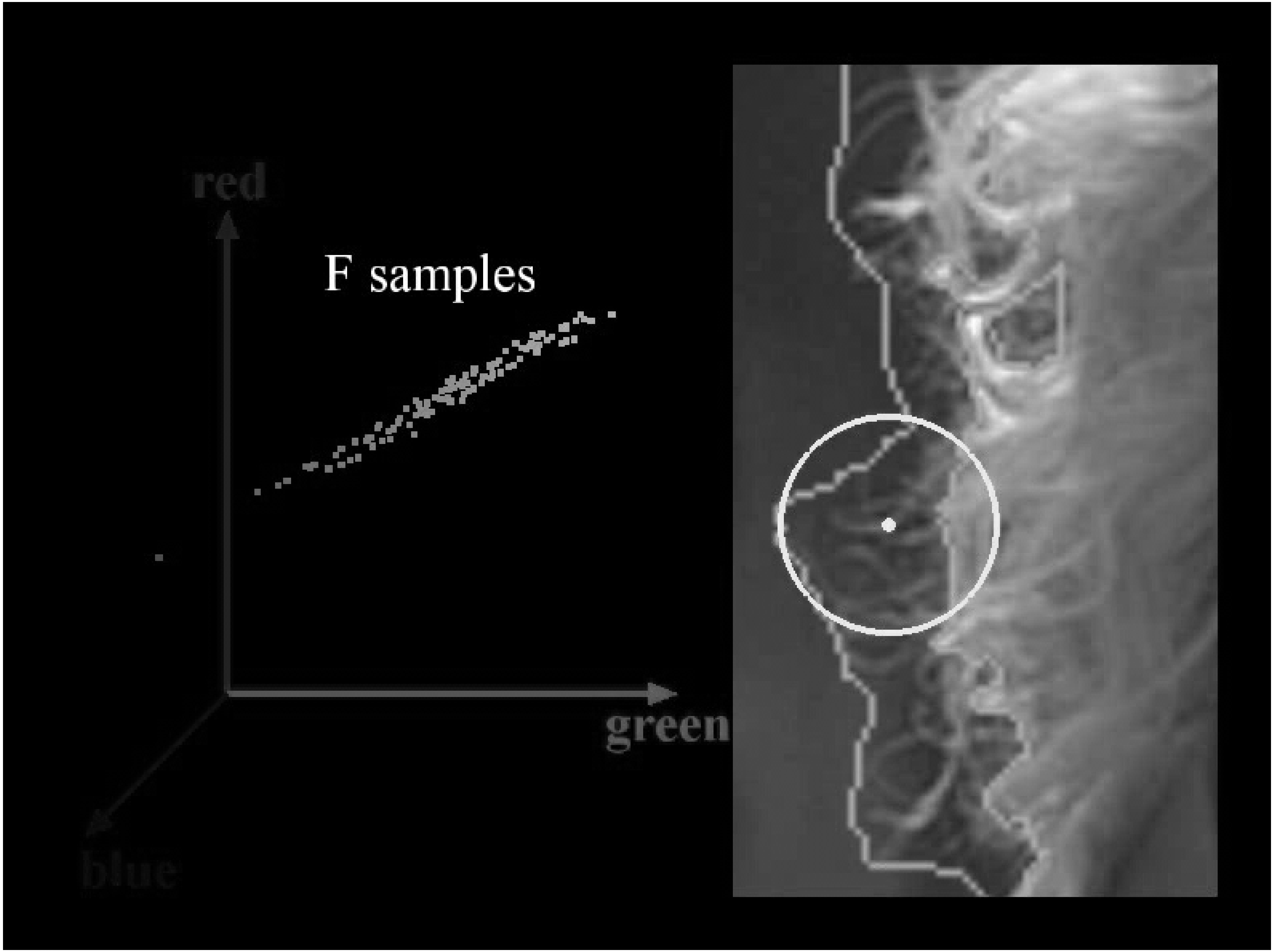
Bayesian image matting

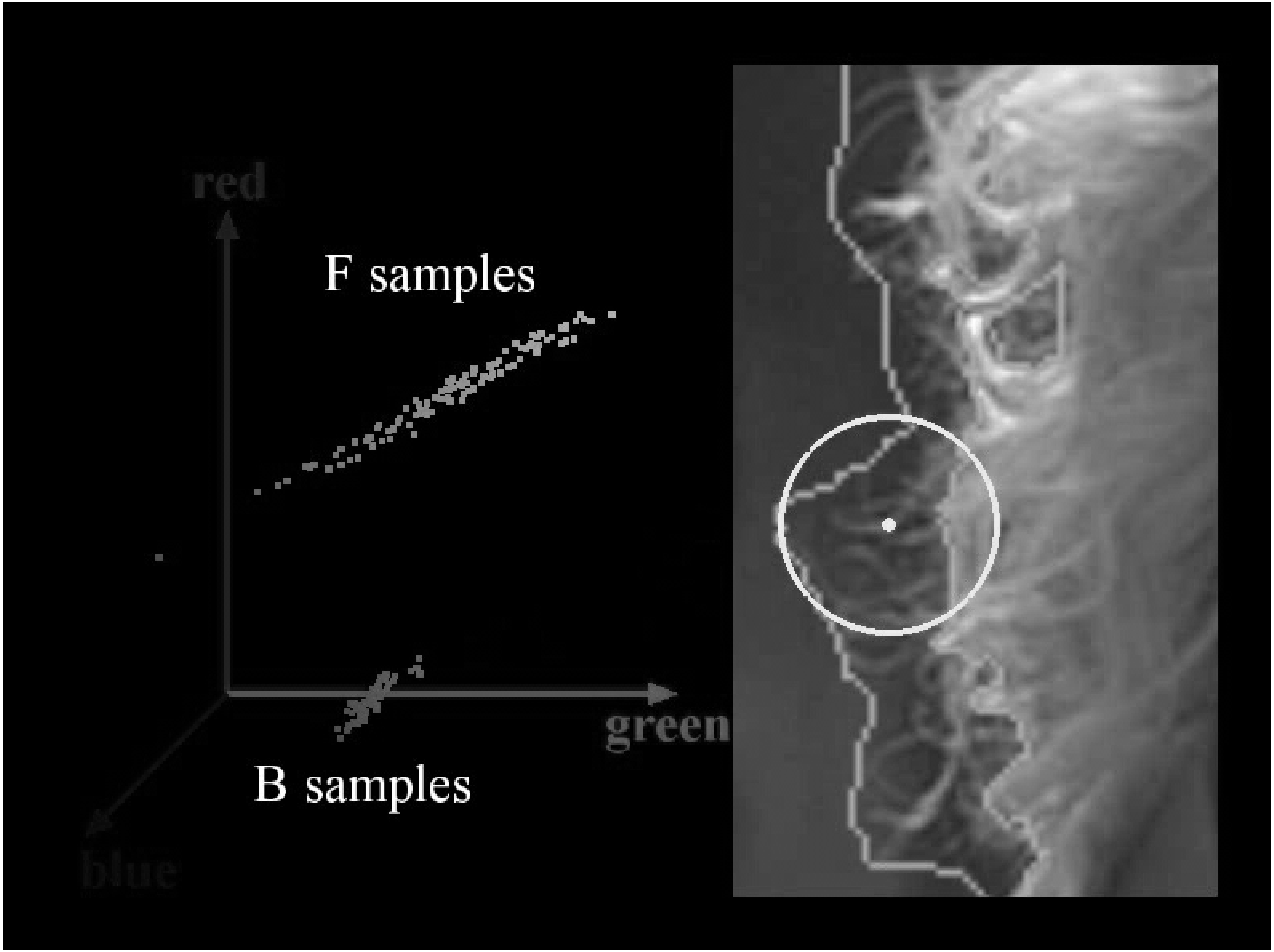

red
green
blue

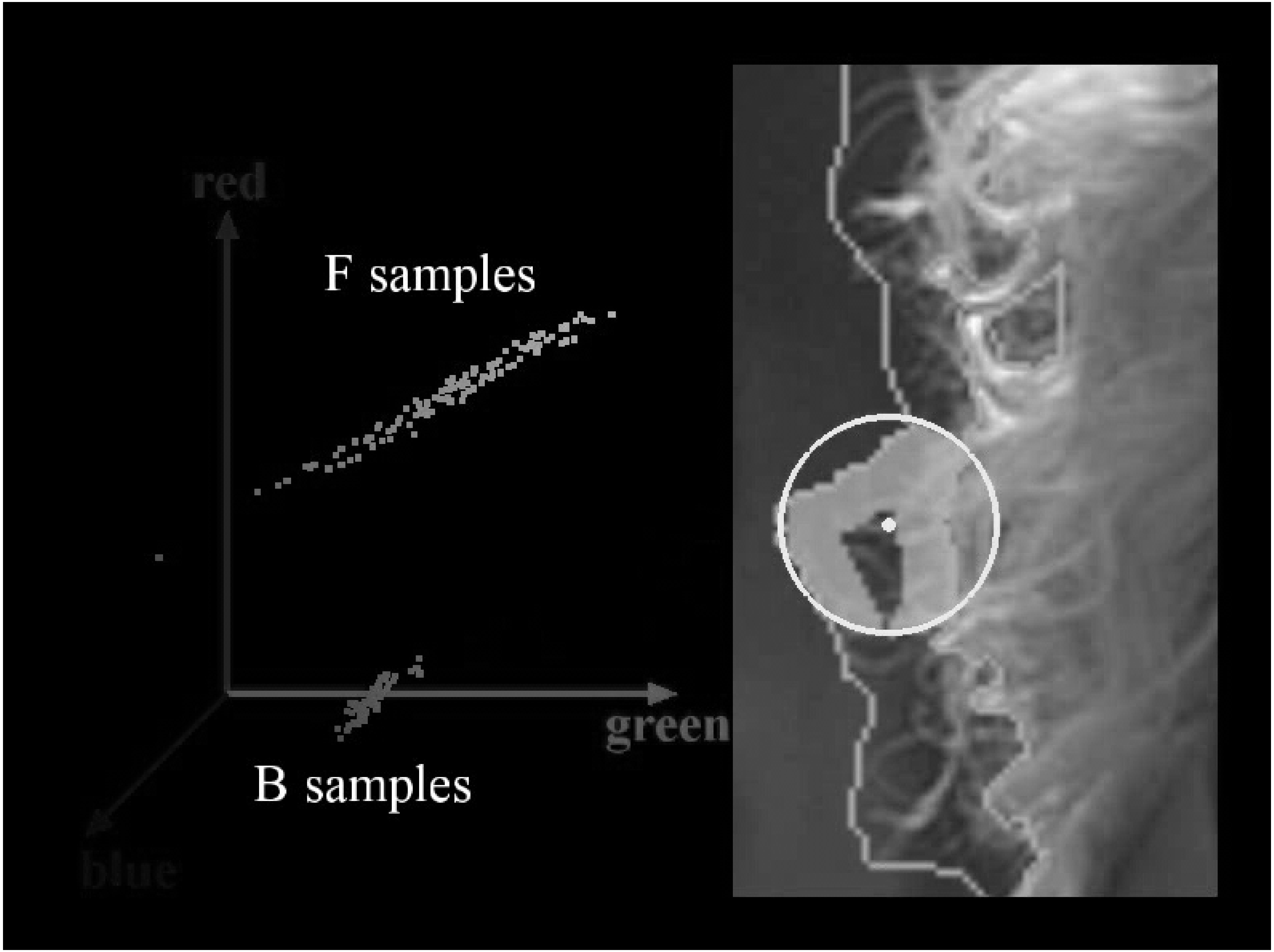


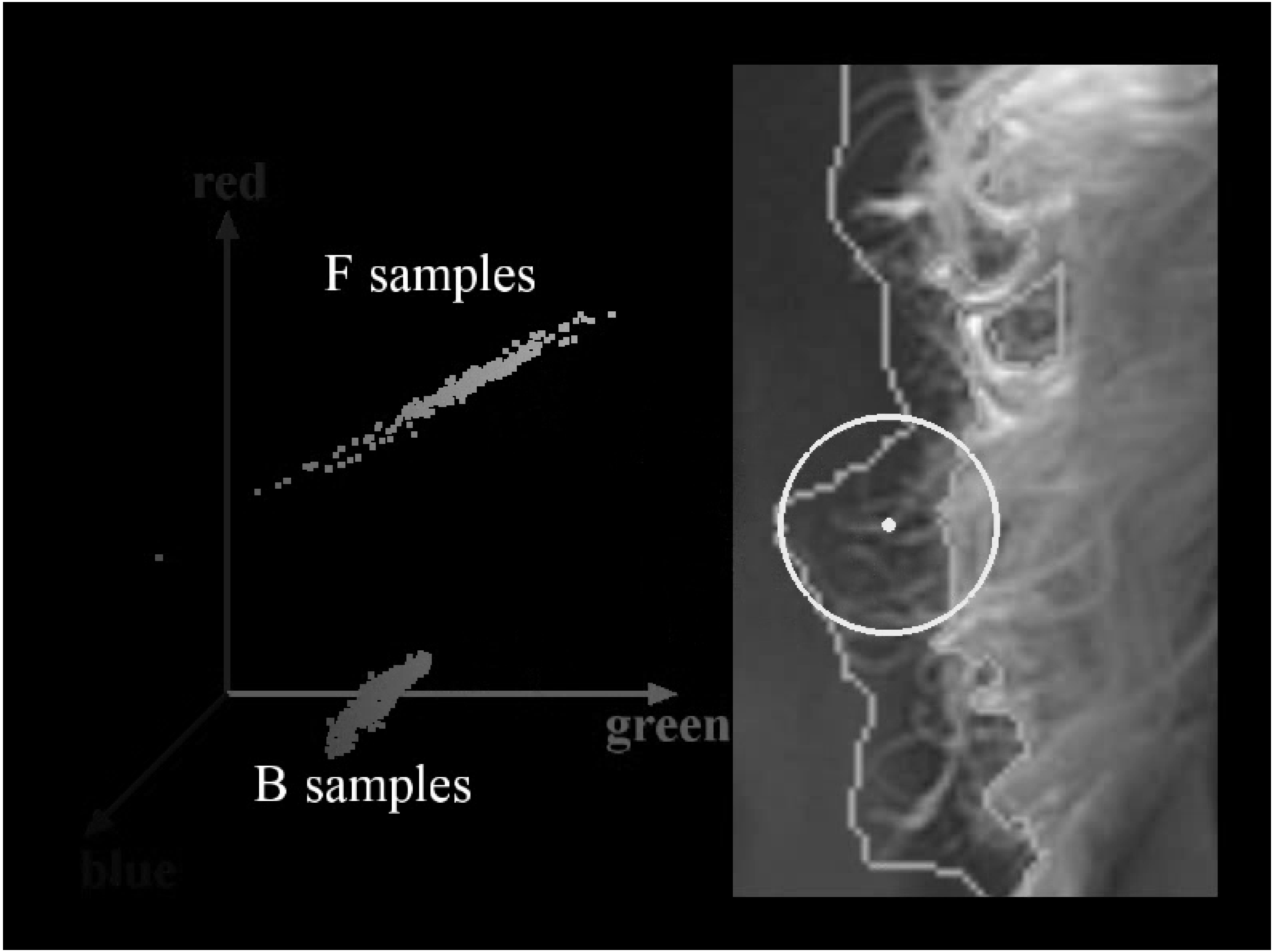
red
green
blue

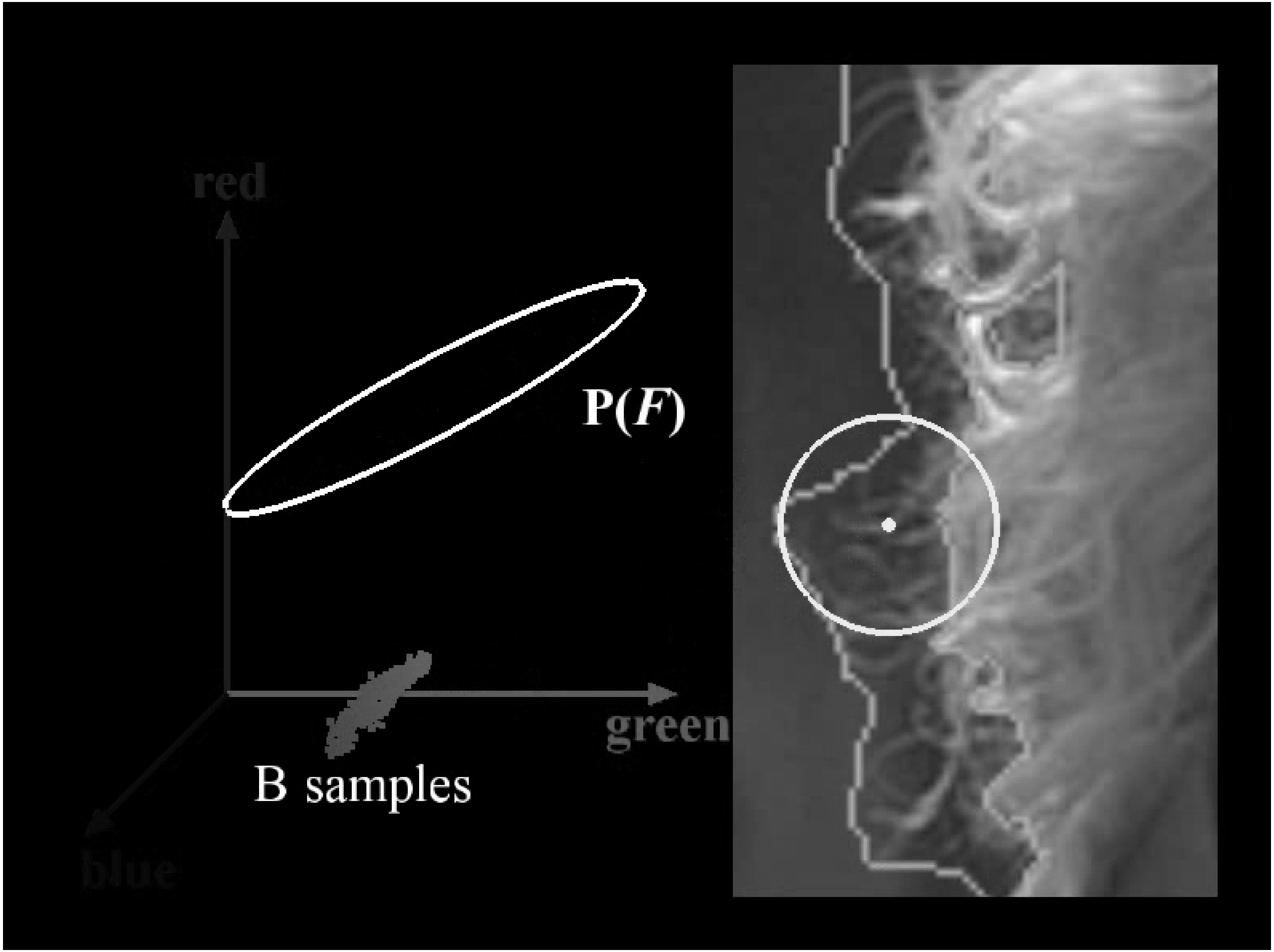

red
green
blue

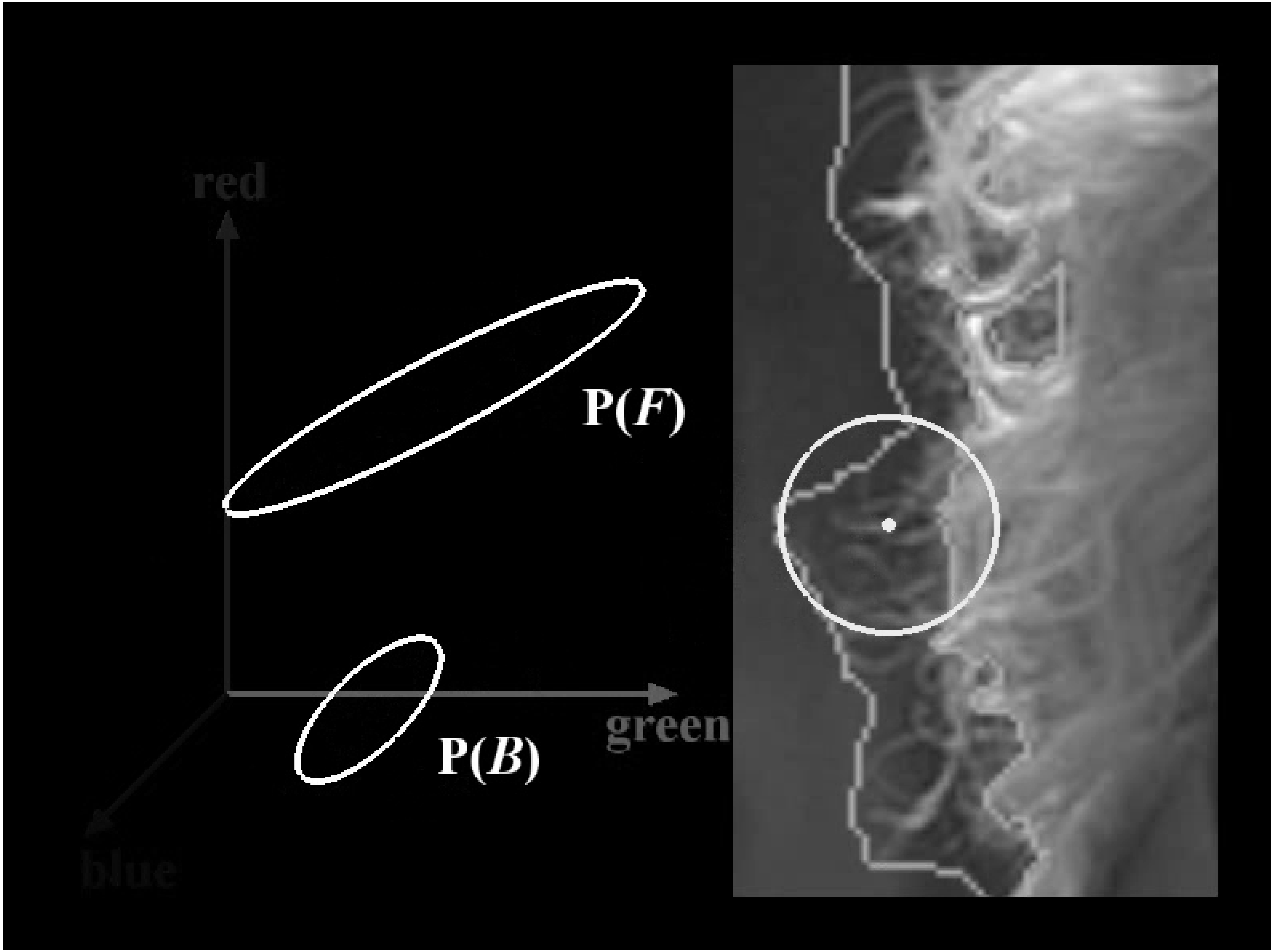

red
F samples
green
blue

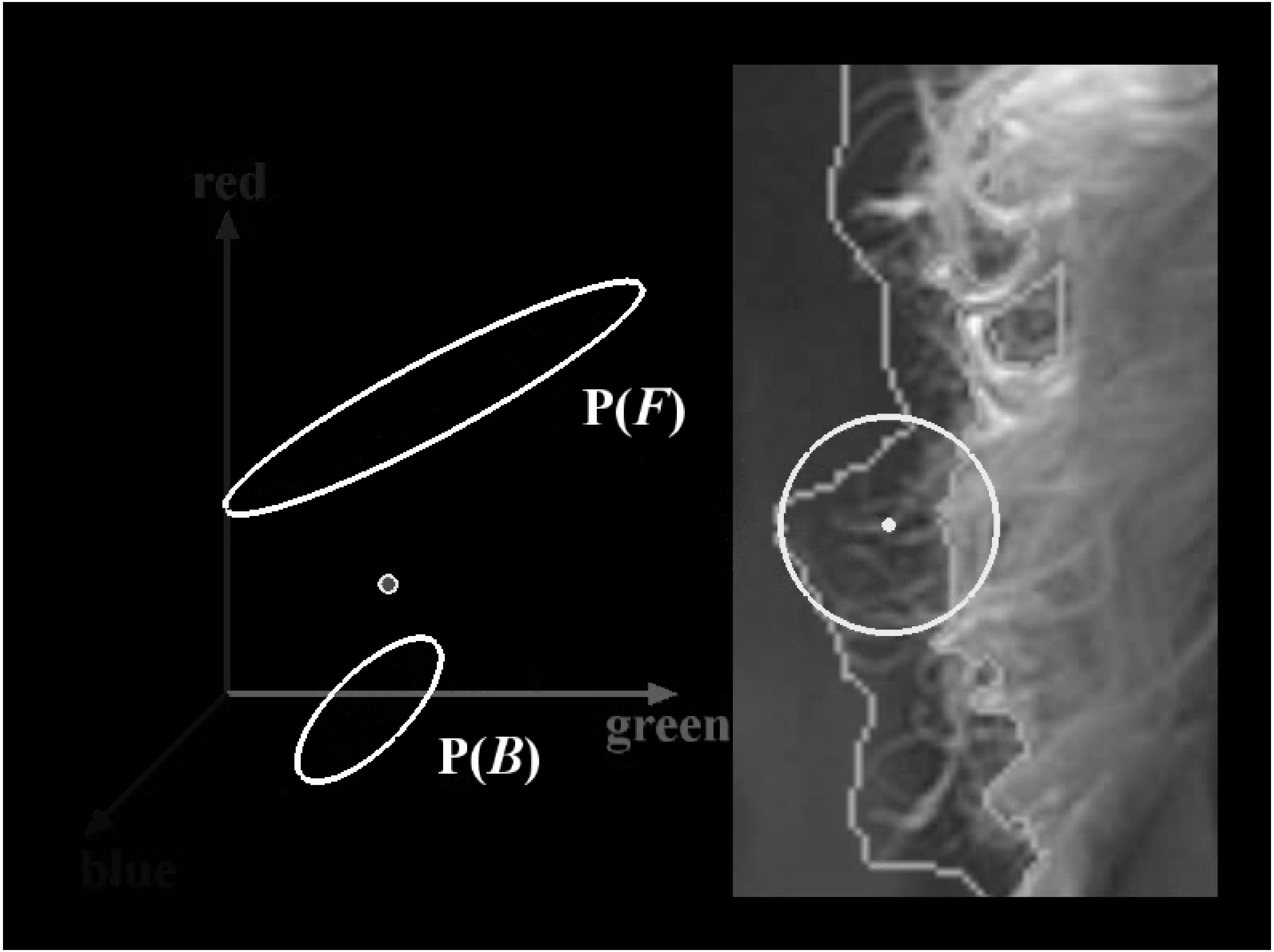

red
F samples
green
B samples
blue

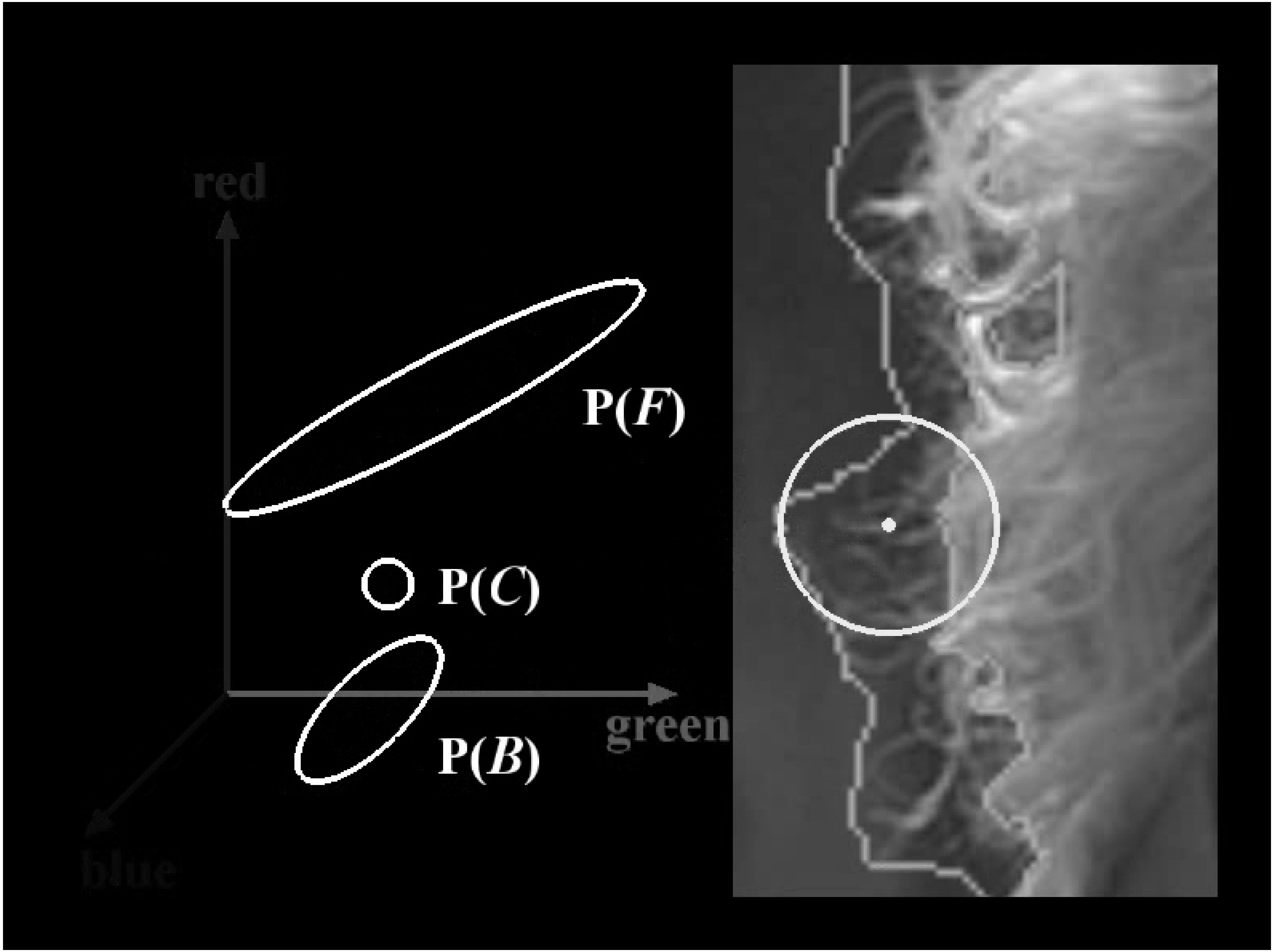

red
F samples
green
B samples
blue


red
F samples
green
B samples
blue

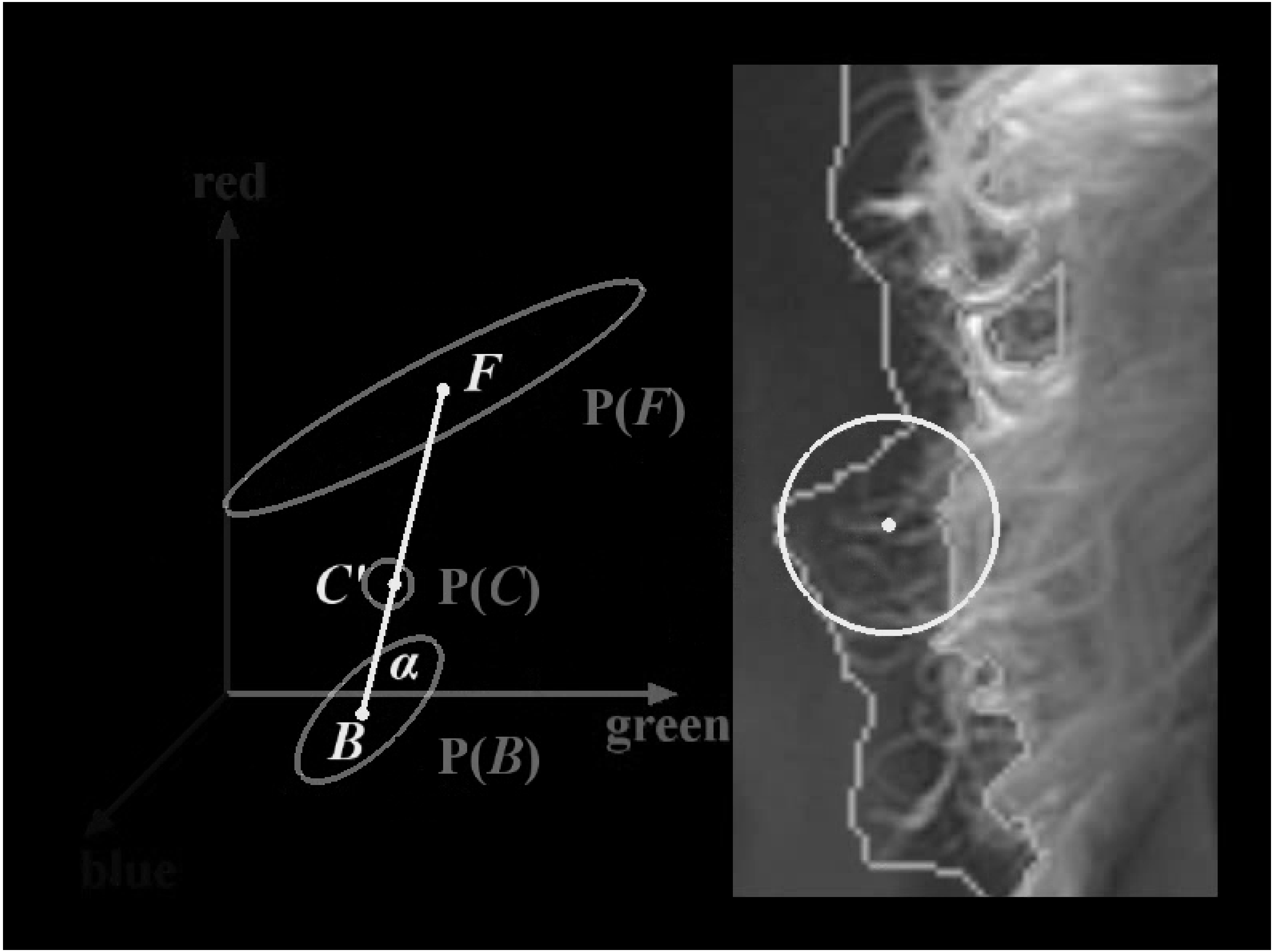

red
P(F)
green
B samples
blue


red
P(F)
P(B)
green
blue


red
P(F)
P(B)
green
blue



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


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

Demo

alpha

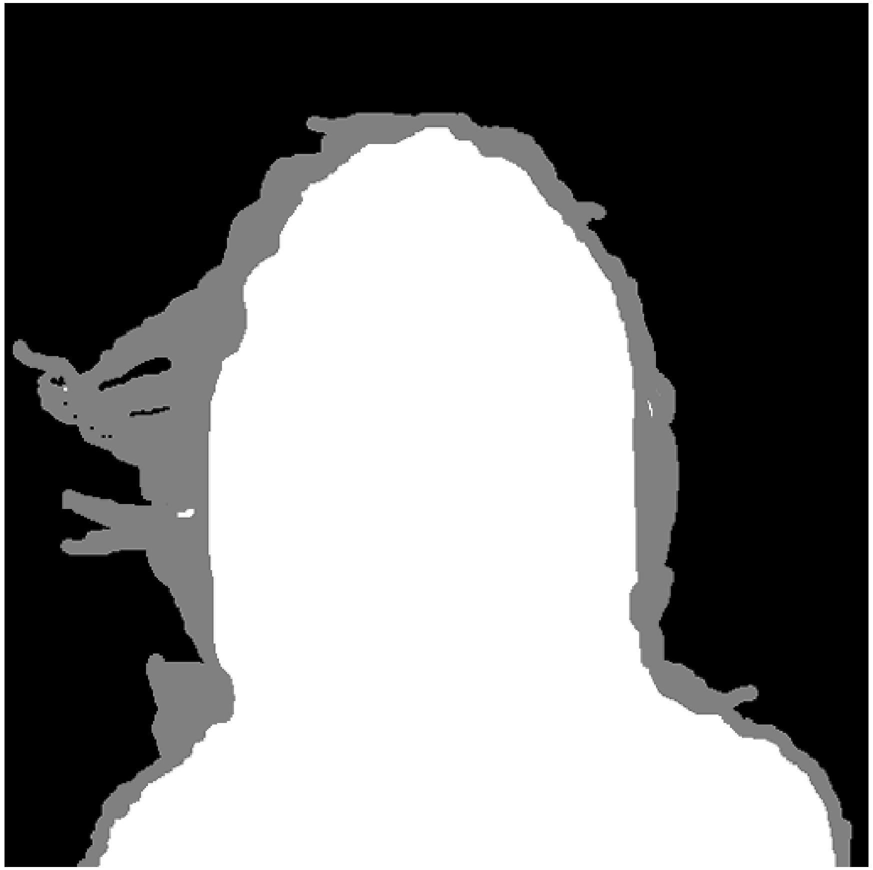
Results

input

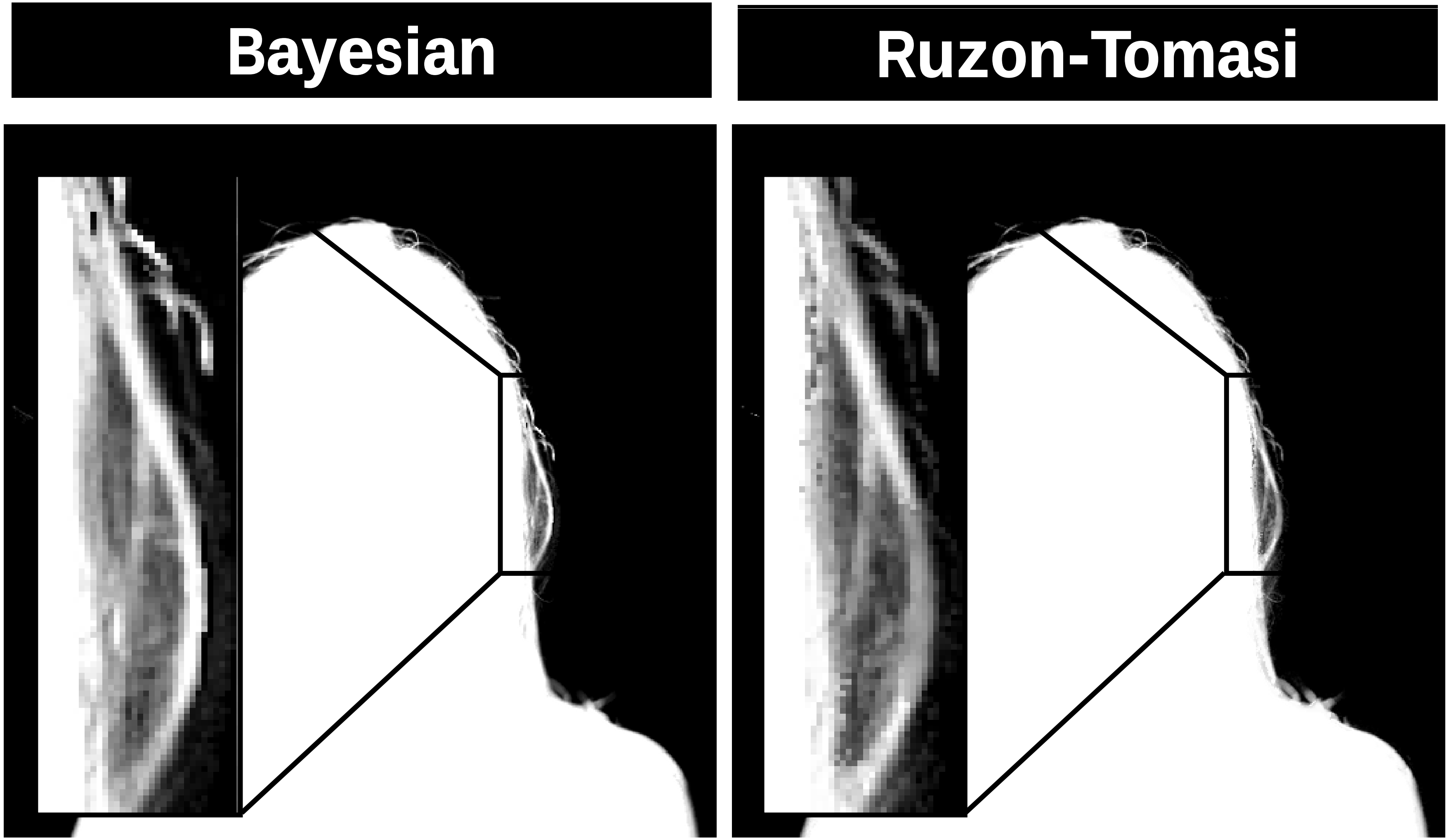
composite

Results

trimap

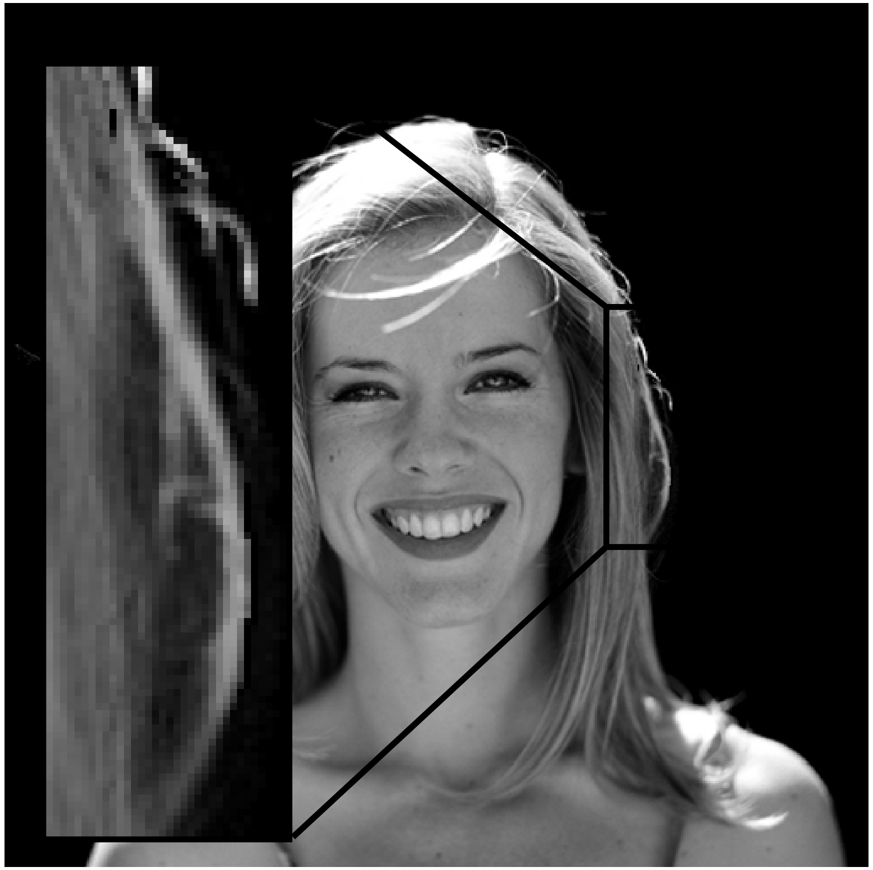


Comparisons



Comparisons

Bayesian



Ruzon-Tomasi

Comparisons

Mishima

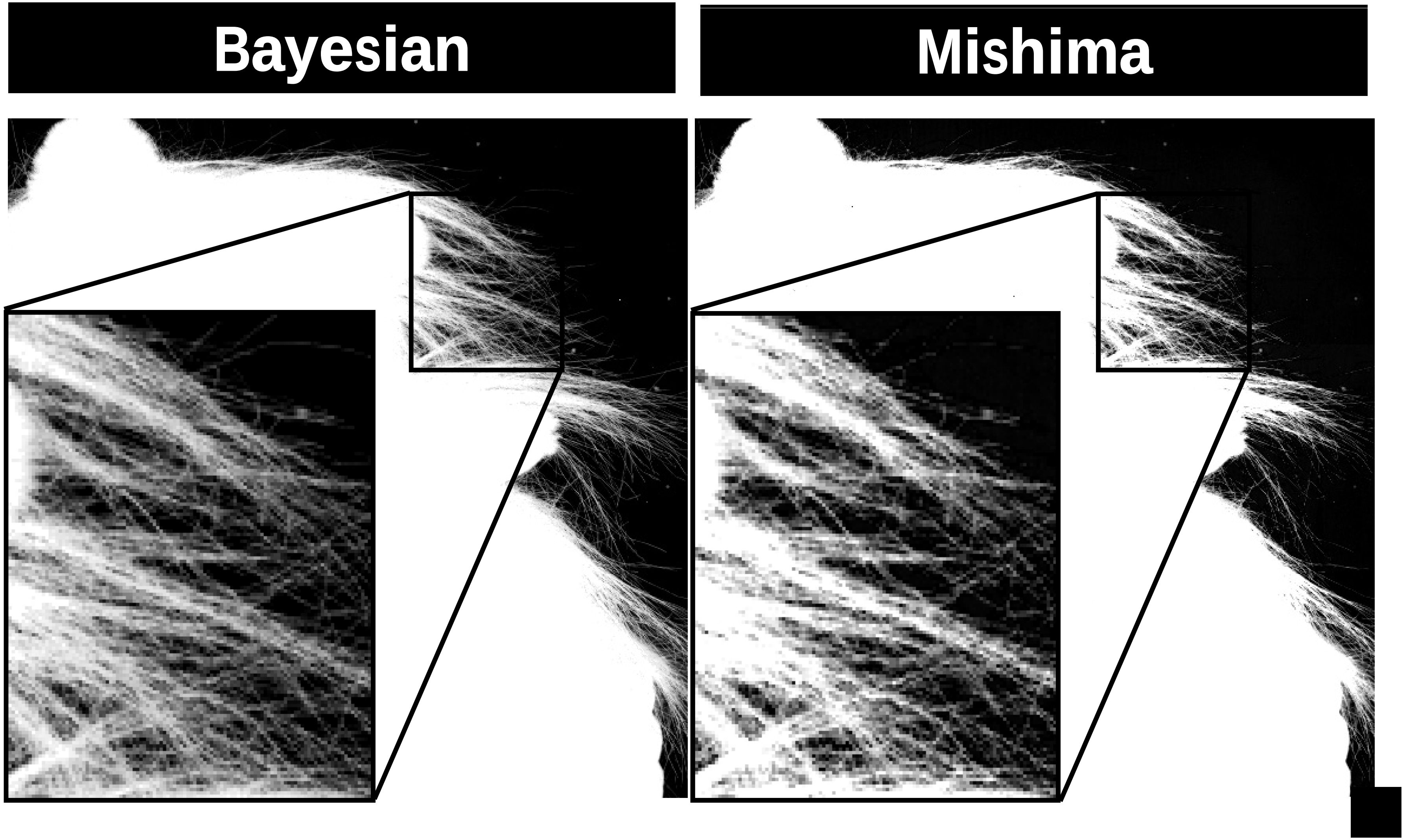
Comparisons

Bayesian

Comparisons

input image

Comparisons



Comparisons

Bayesian

Mishima

Comparisons

input
video

Video matting

input
video

input
key
trimaps

Video matting

input
video

interpo-
lated
trimaps

Video matting

input video

interpo-lated trimaps

output alpha

Video matting

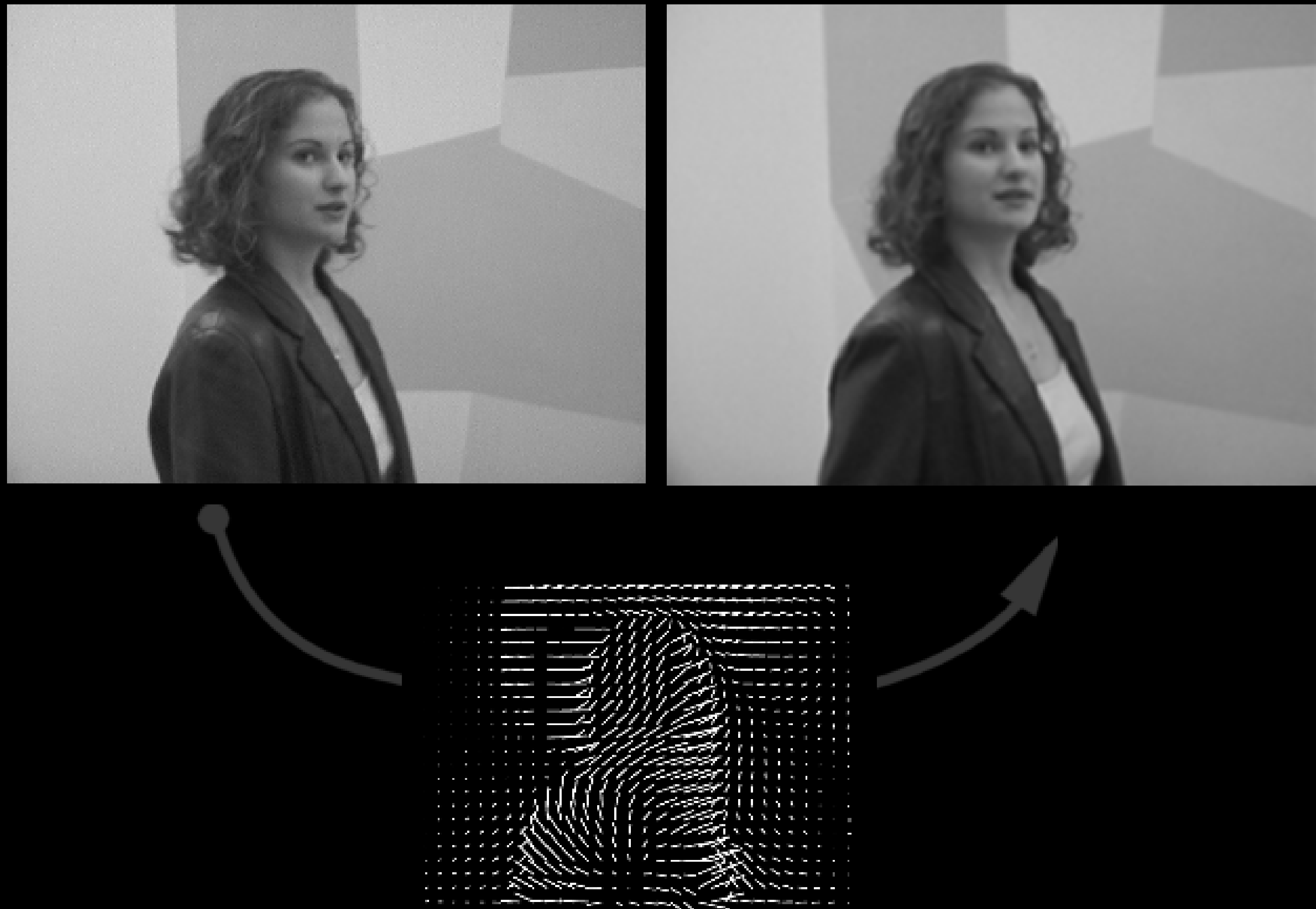
input video

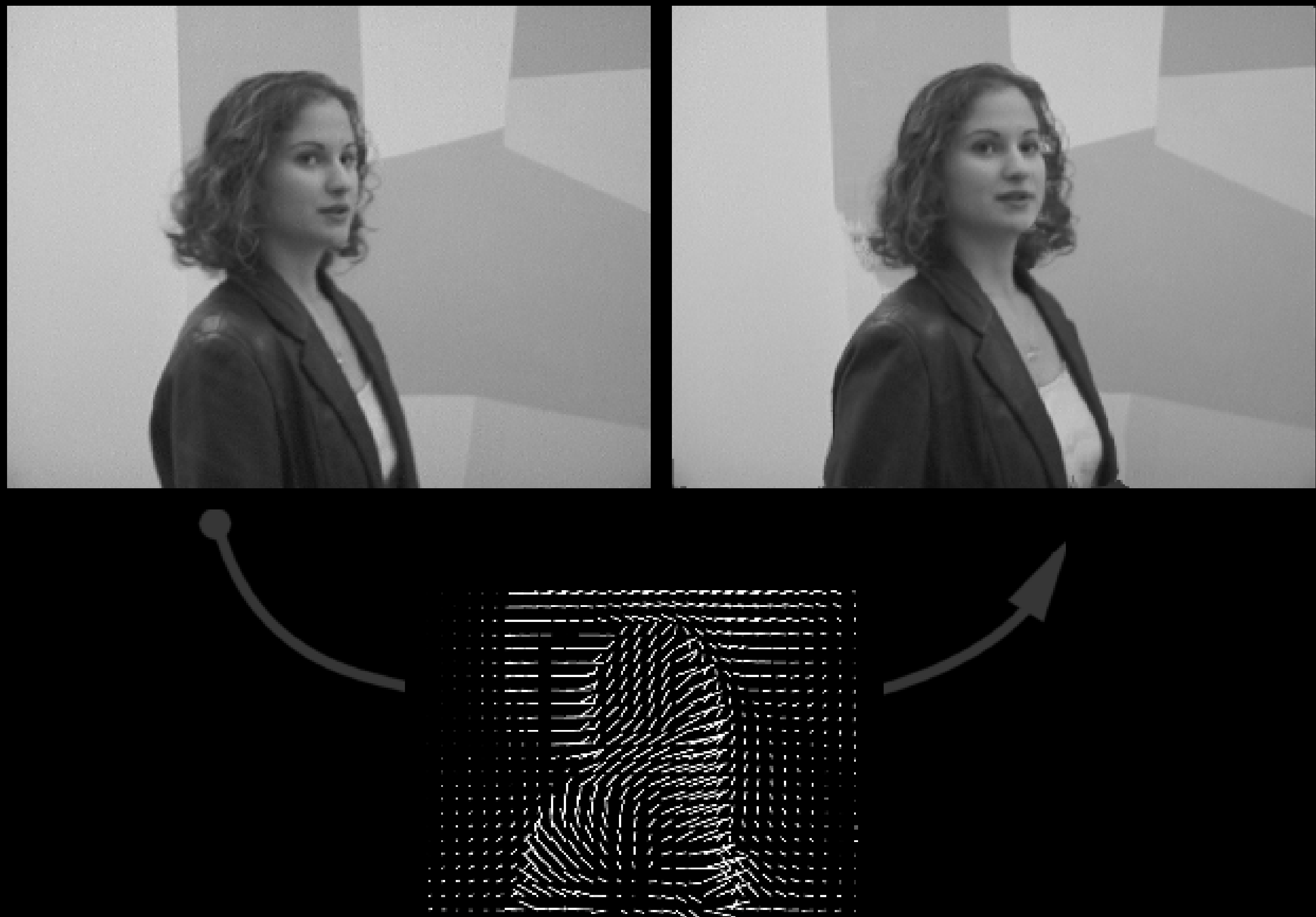
Compo-site

interpo-lated trimaps

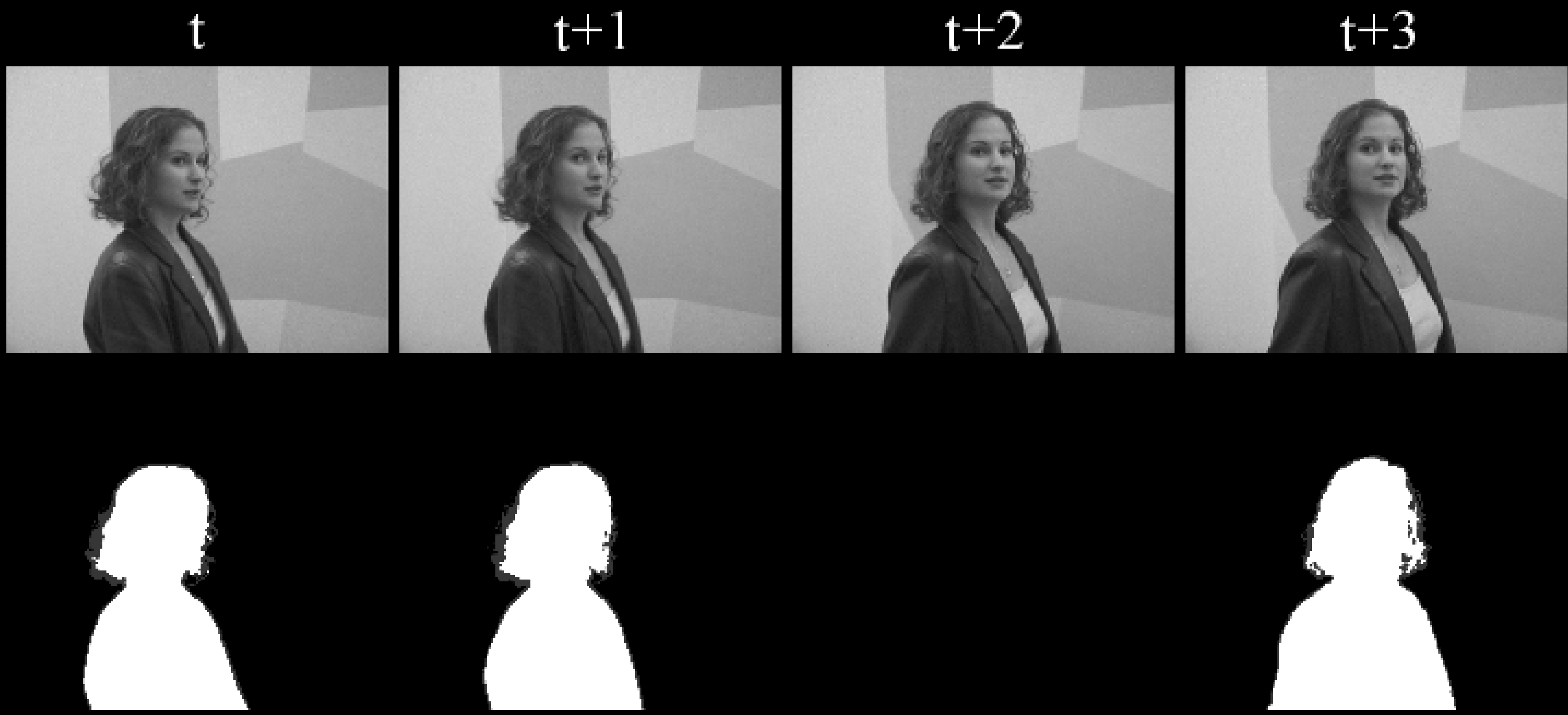
output alpha

Video matting




t
t+1
t+2
t+3


t
t+1
t+2
t+3

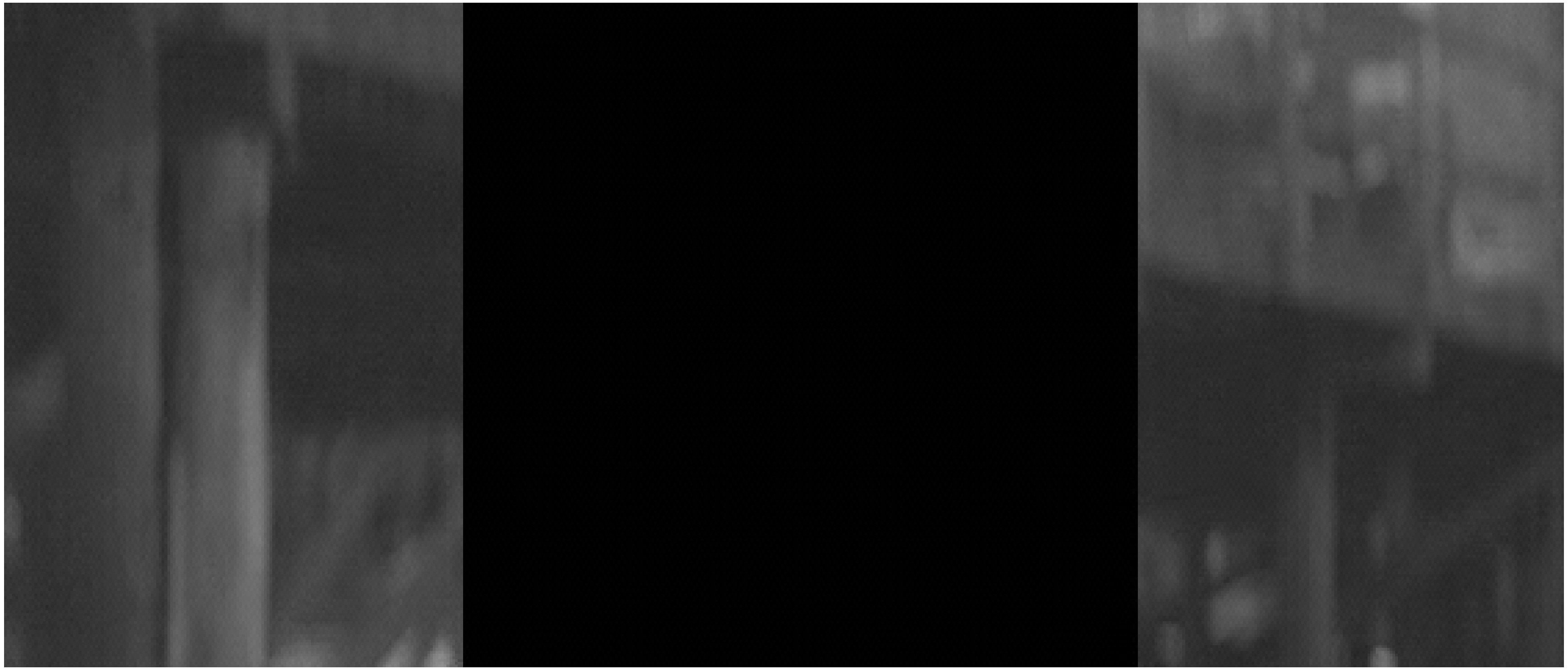

t
t+1
t+2
t+3


t
t+1
t+2
t+3

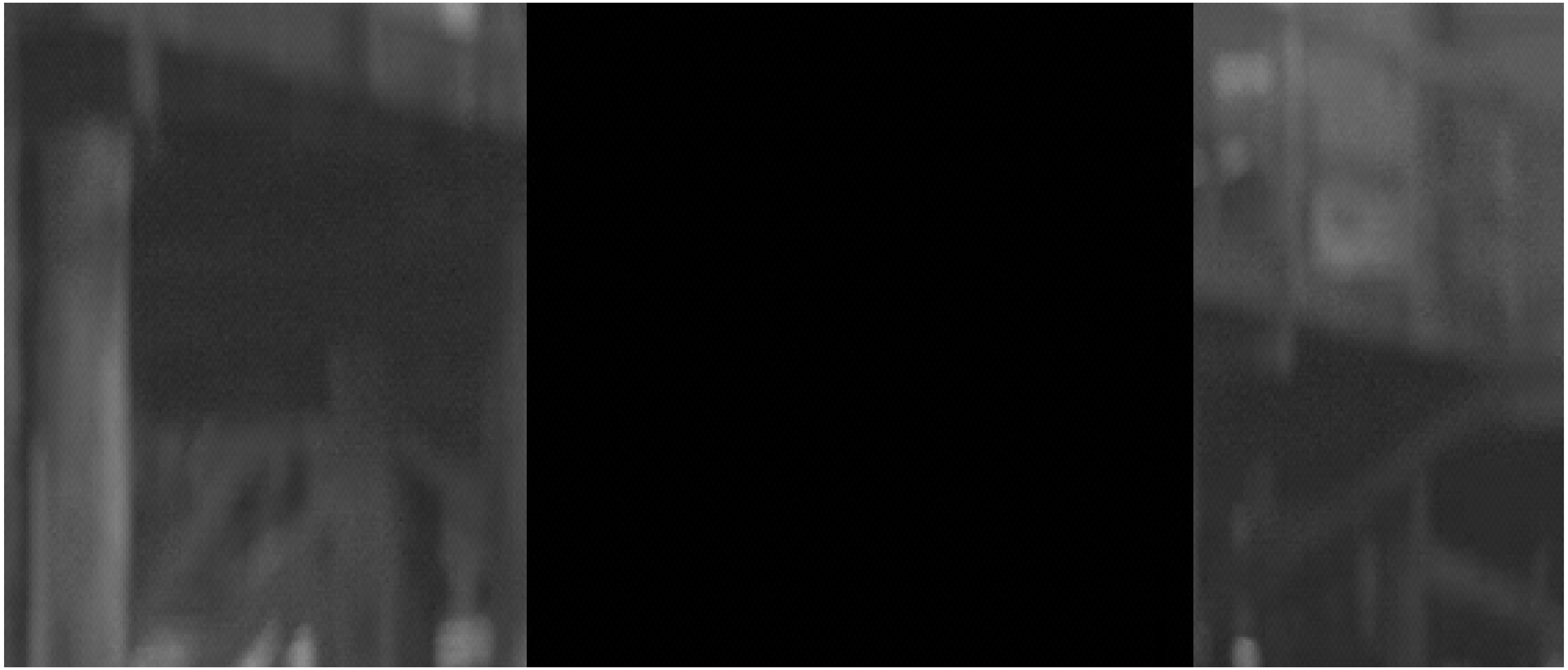

t
t+1
t+2
t+3

Sample composite

Garbage mattes



Garbage mattes



Background estimation

Background estimation

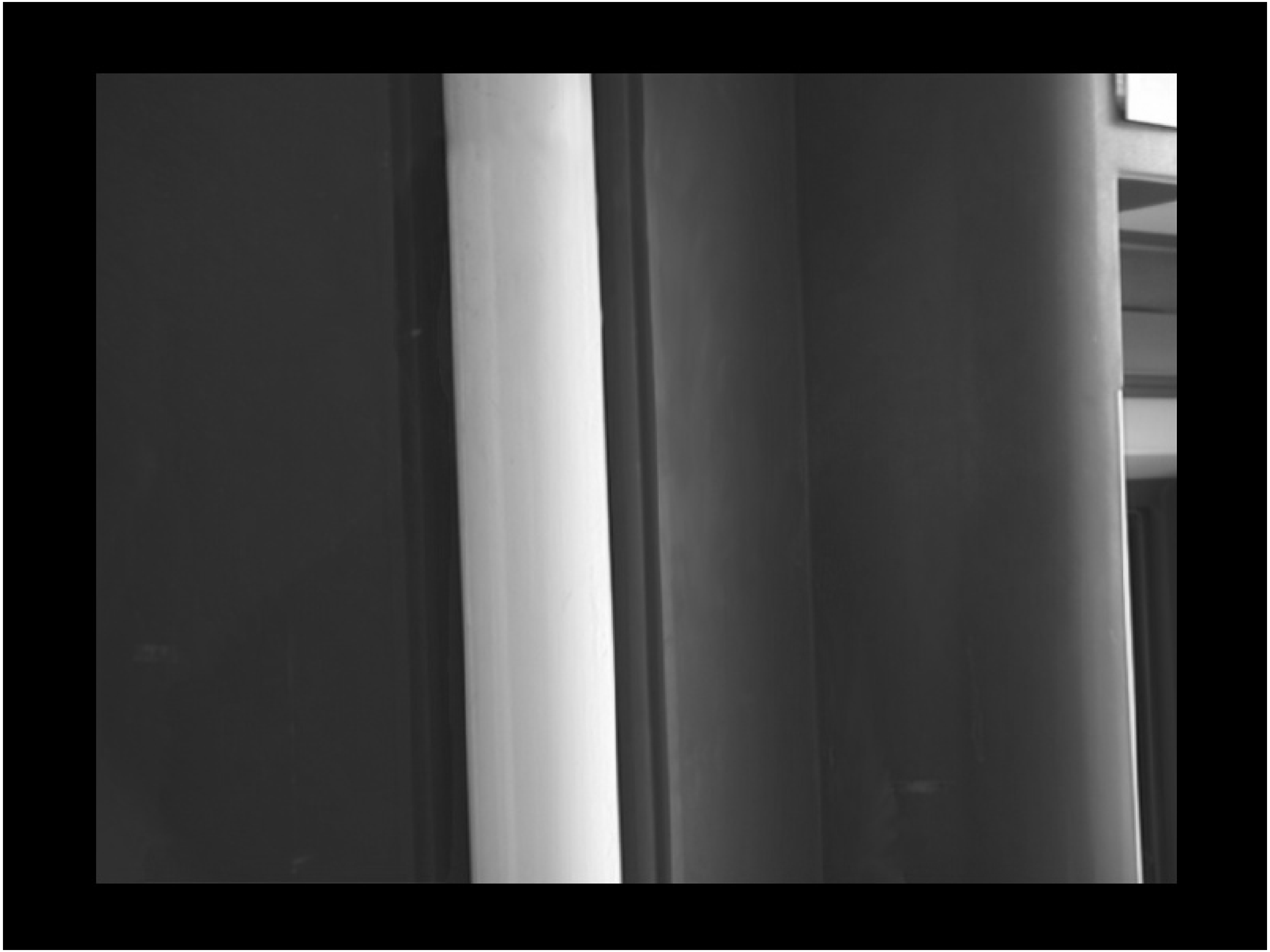
Alpha matte

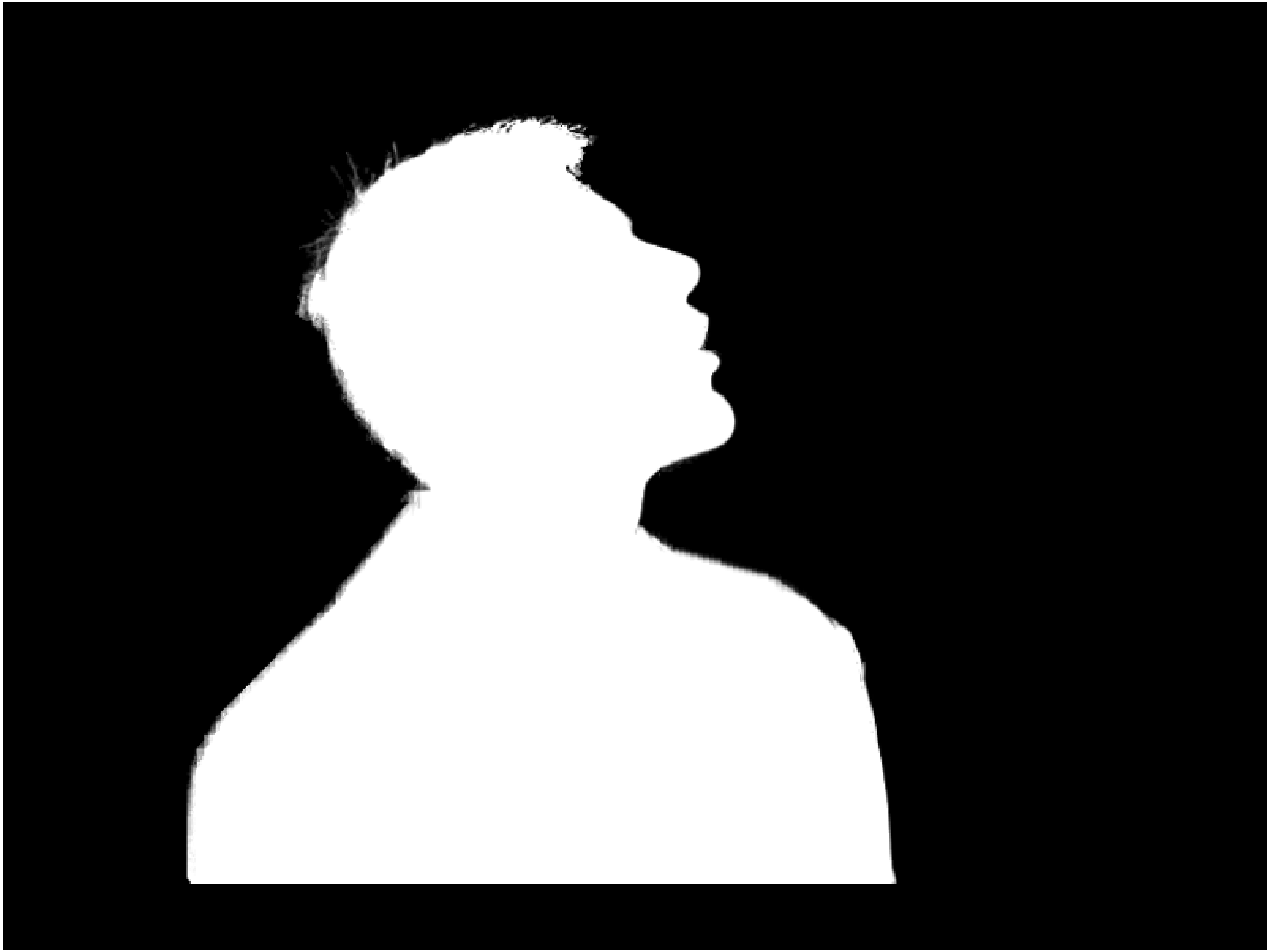
without background

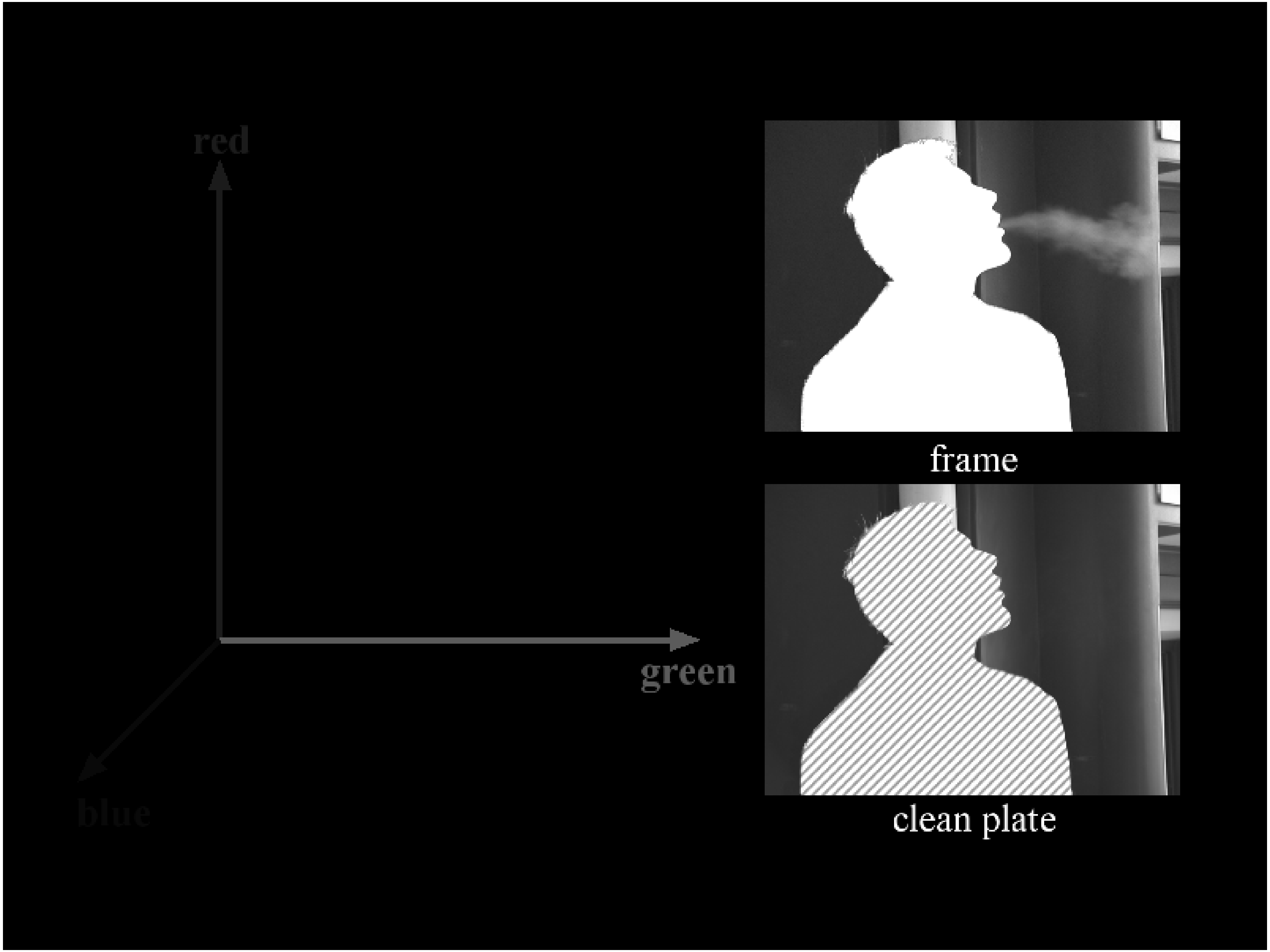
with background

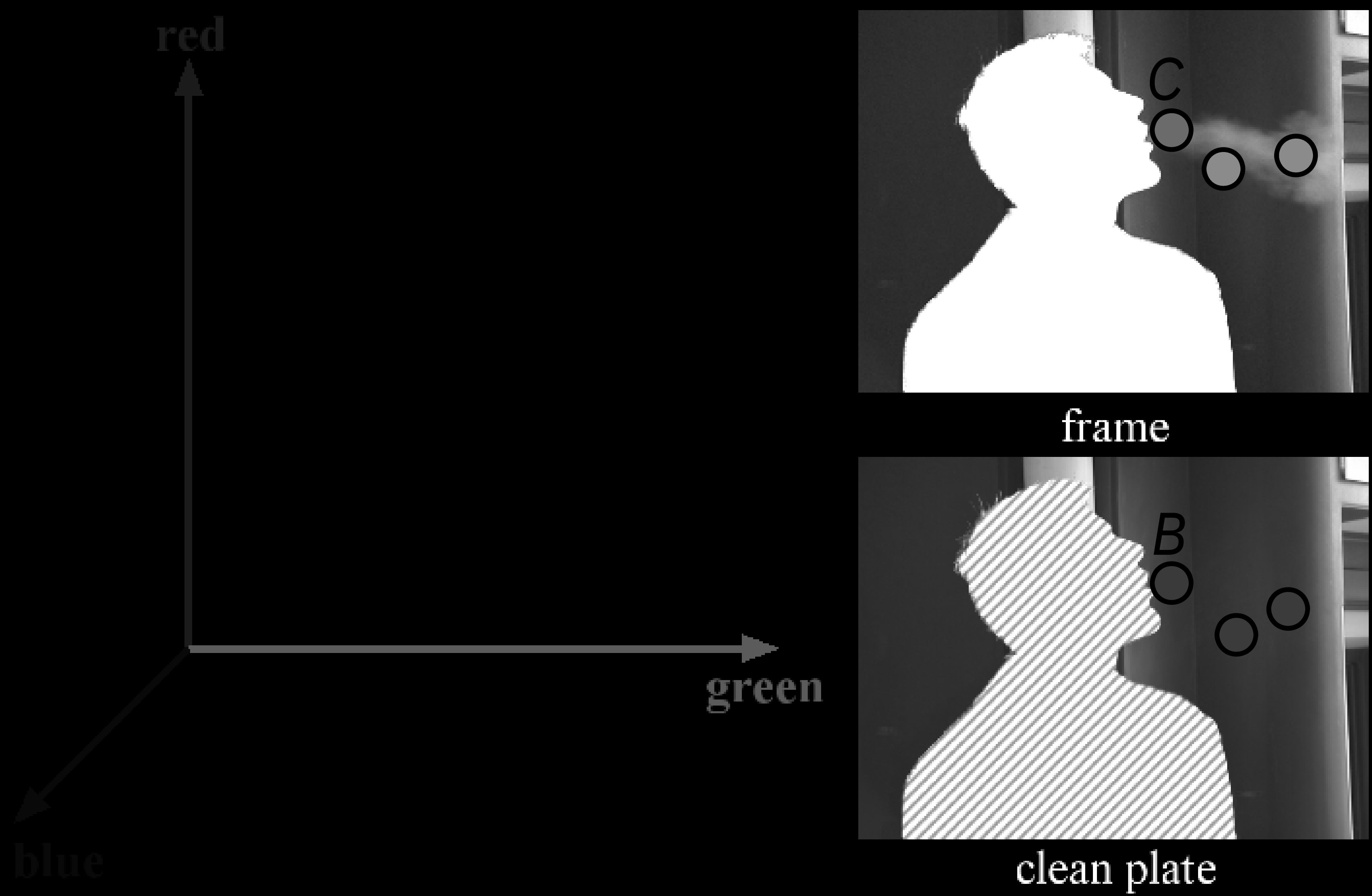
Comparison


input
composite






red
green
blue
frame
clean plate


red
green
blue
C
frame
B
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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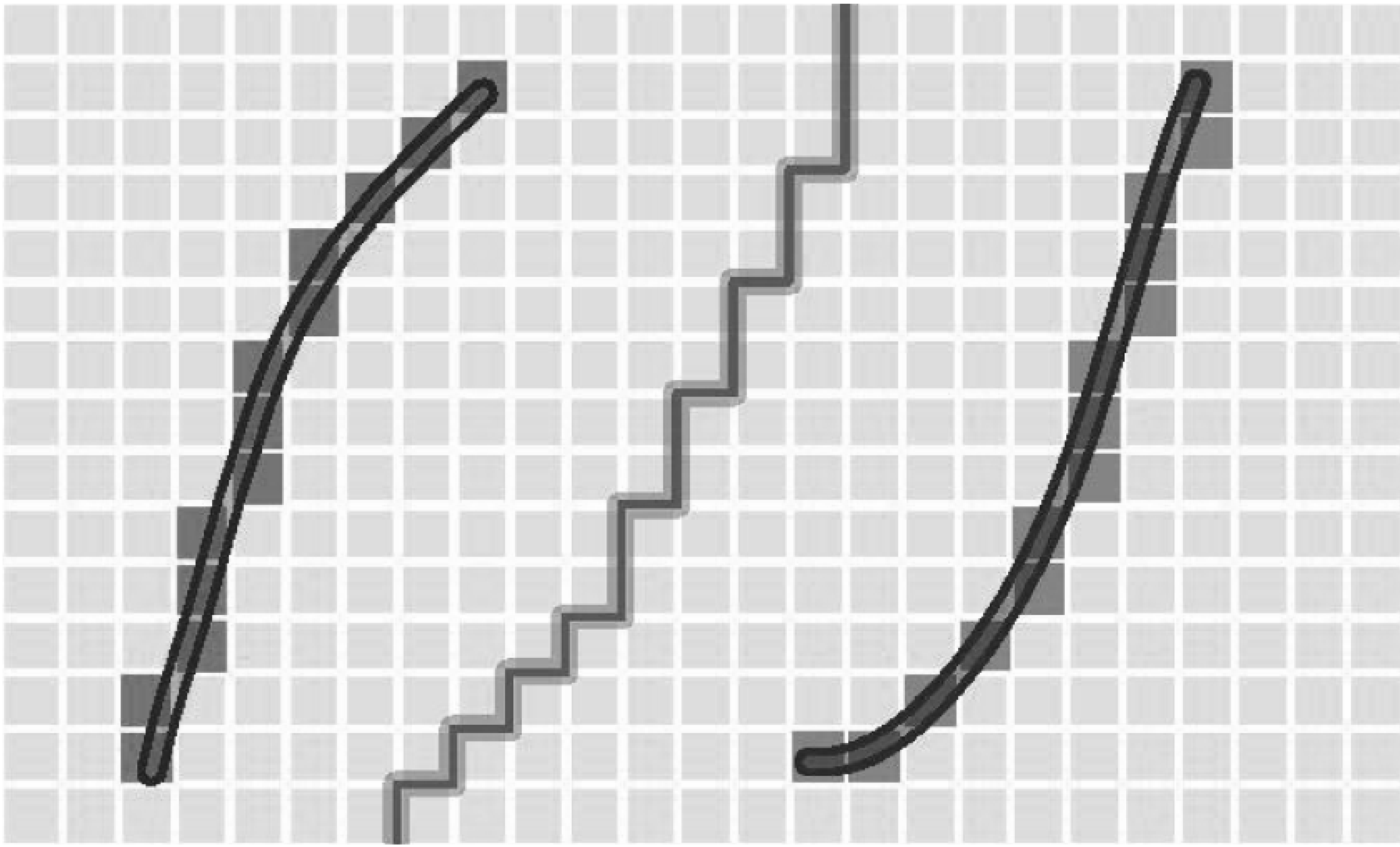
Scribble-based input

trimap

scribble

Motivation

LazySnapping



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

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

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

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

LazySnapping

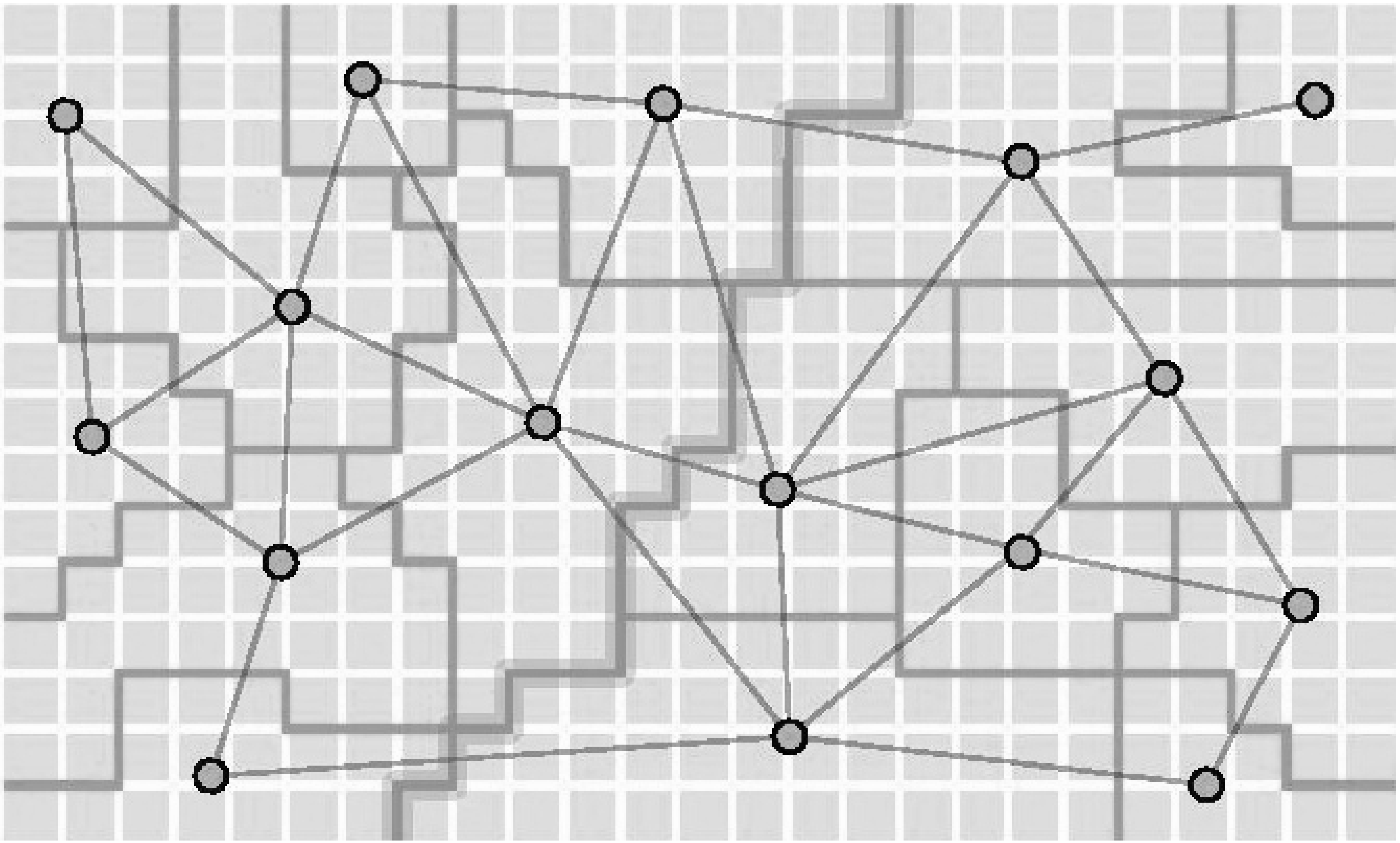
$$E(X) = \sum_{i \in \mathcal{V}} E_1(x_i) + \lambda \sum_{(i,j) \in \mathcal{E}} \boxed{E_2(x_i, x_j)}$$

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

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

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

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

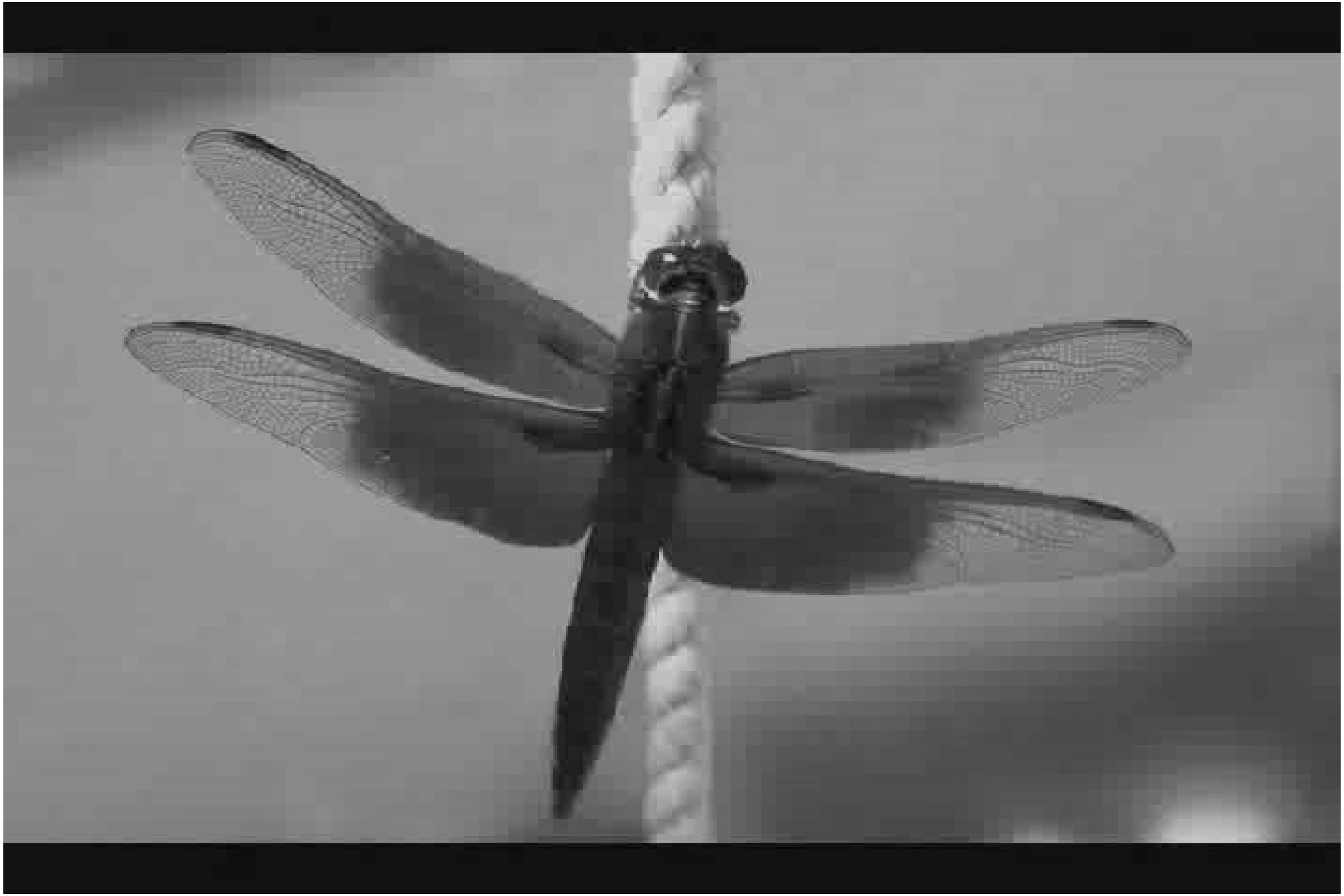
$$I = \alpha F + (1 - \alpha) B$$

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

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

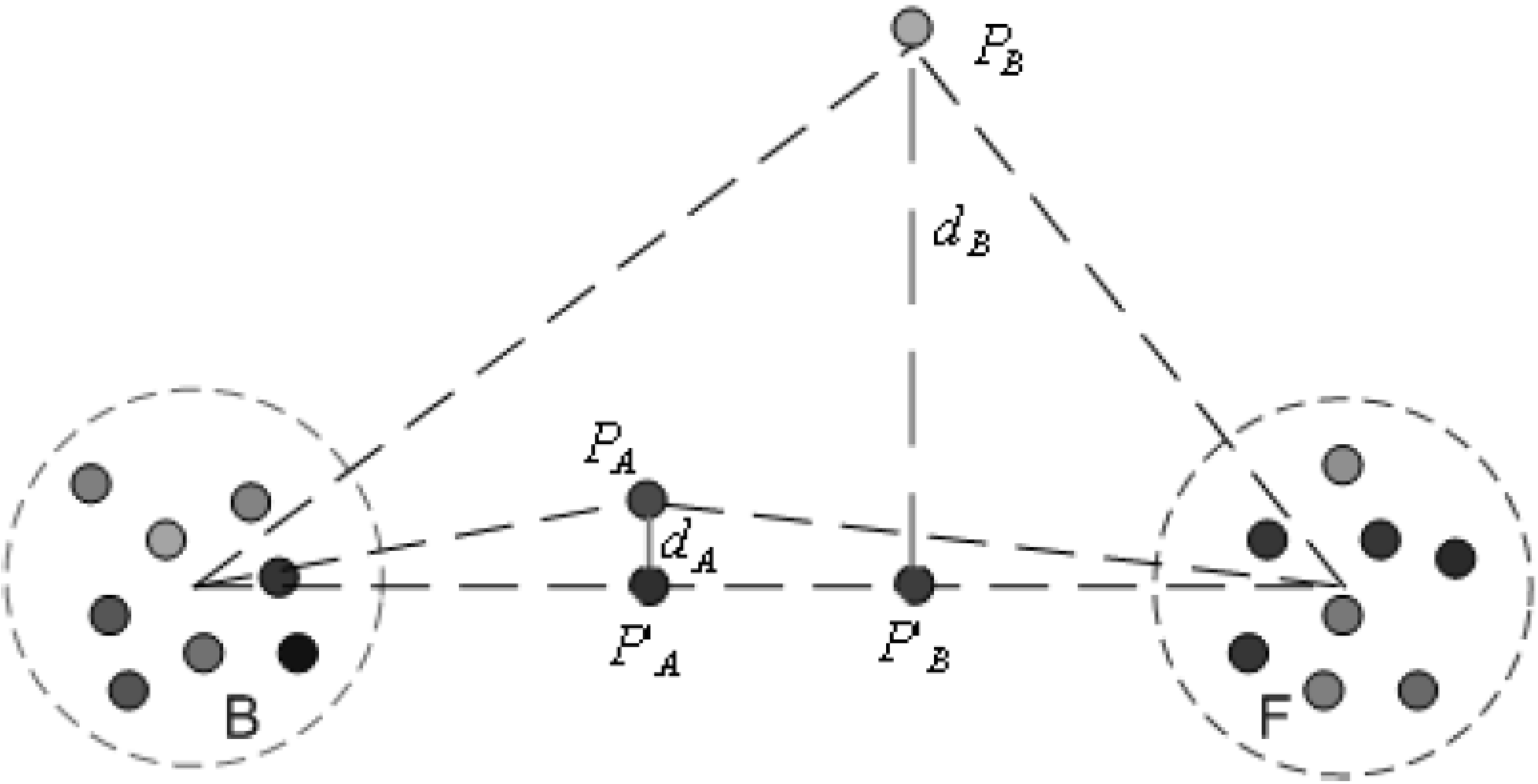
$$\alpha^* = \arg\min_{\alpha} \int\int_{p \in \Omega} ||\nabla \alpha_p - \frac{1}{F_p - B_p} \nabla I_p||^2 dp$$

Poisson matting



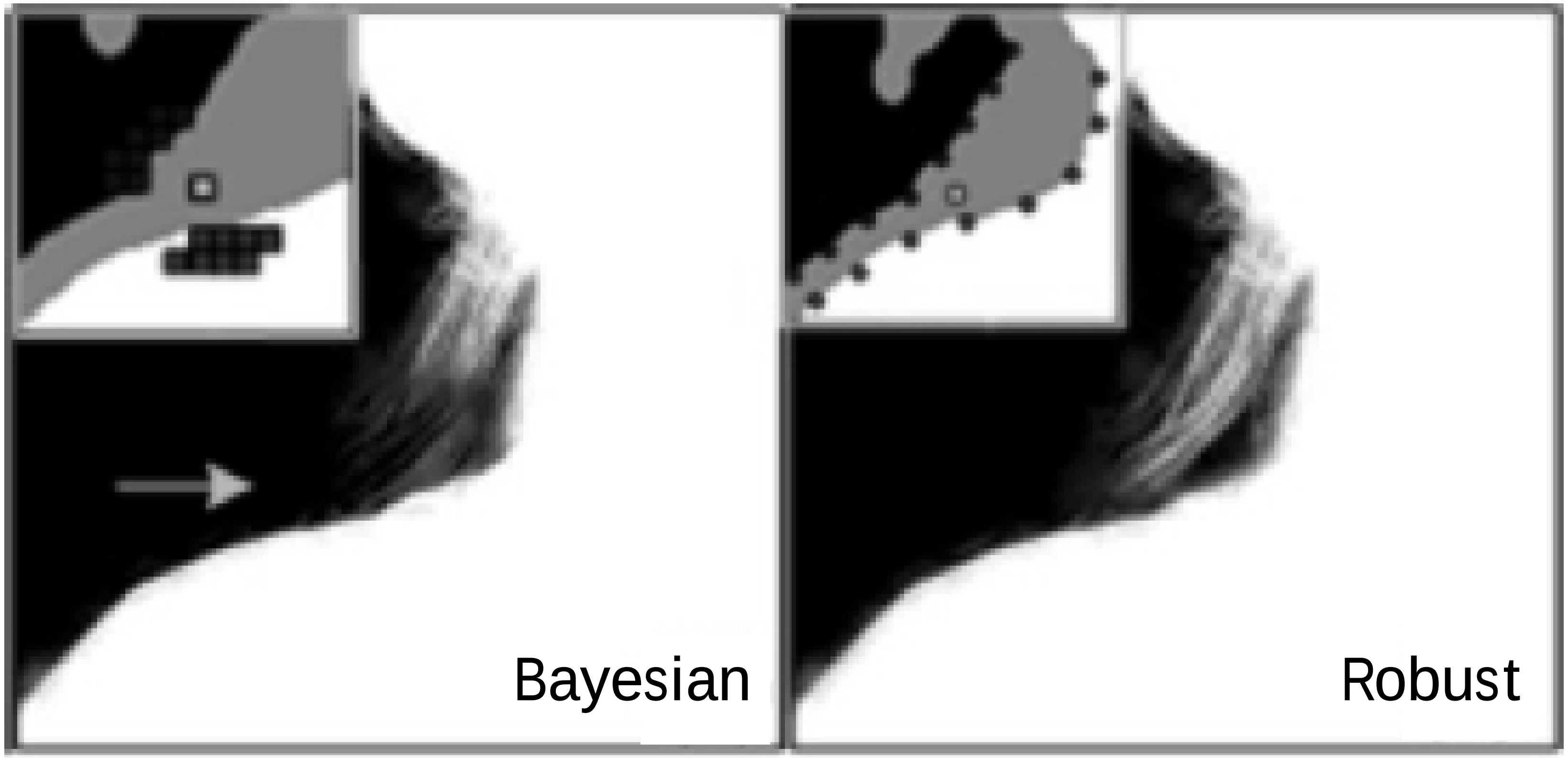
Robust matting

- Jue Wang and Michael Cohen, CVPR 2007



Robust matting

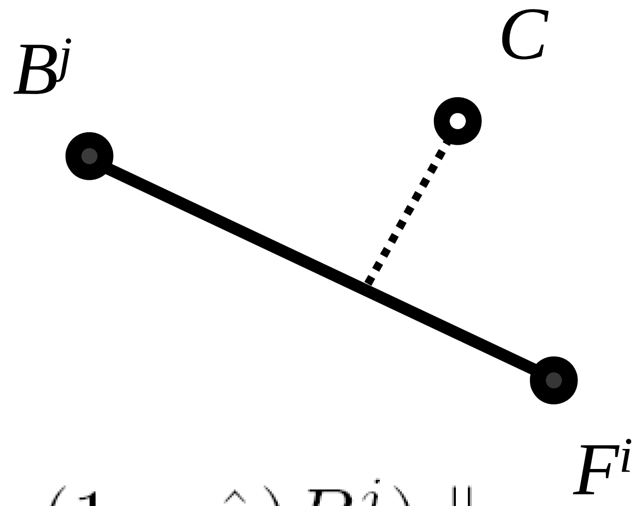
- Instead of fitting models, a non-parametric approach is used



Robust matting

- We must evaluate hypothesized foreground/background pairs

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

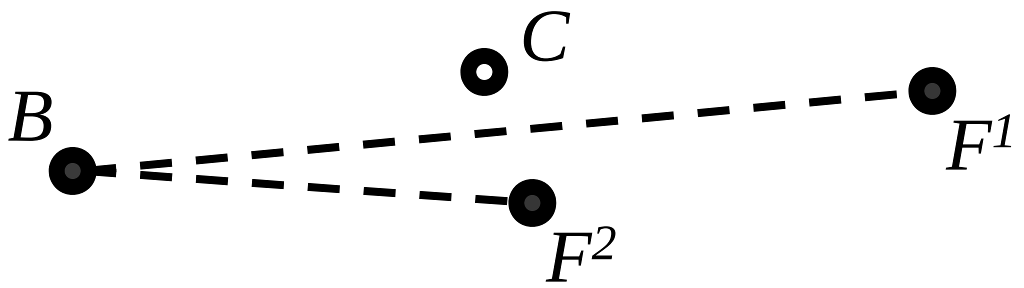


distance ratio

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

Robust matting

- To encourage pure fg/bg pixels, add weights



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

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

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

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

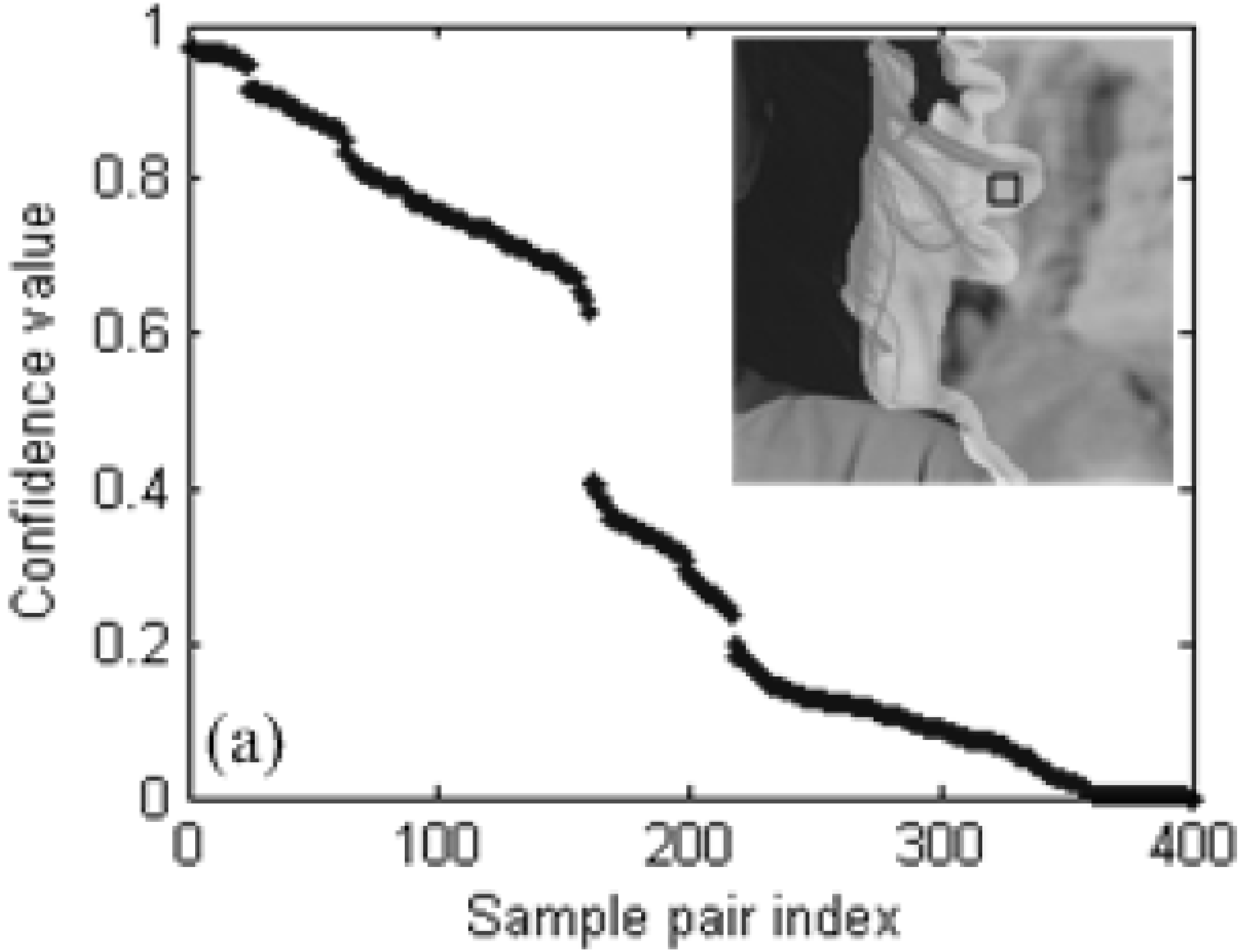
Robust matting

- 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

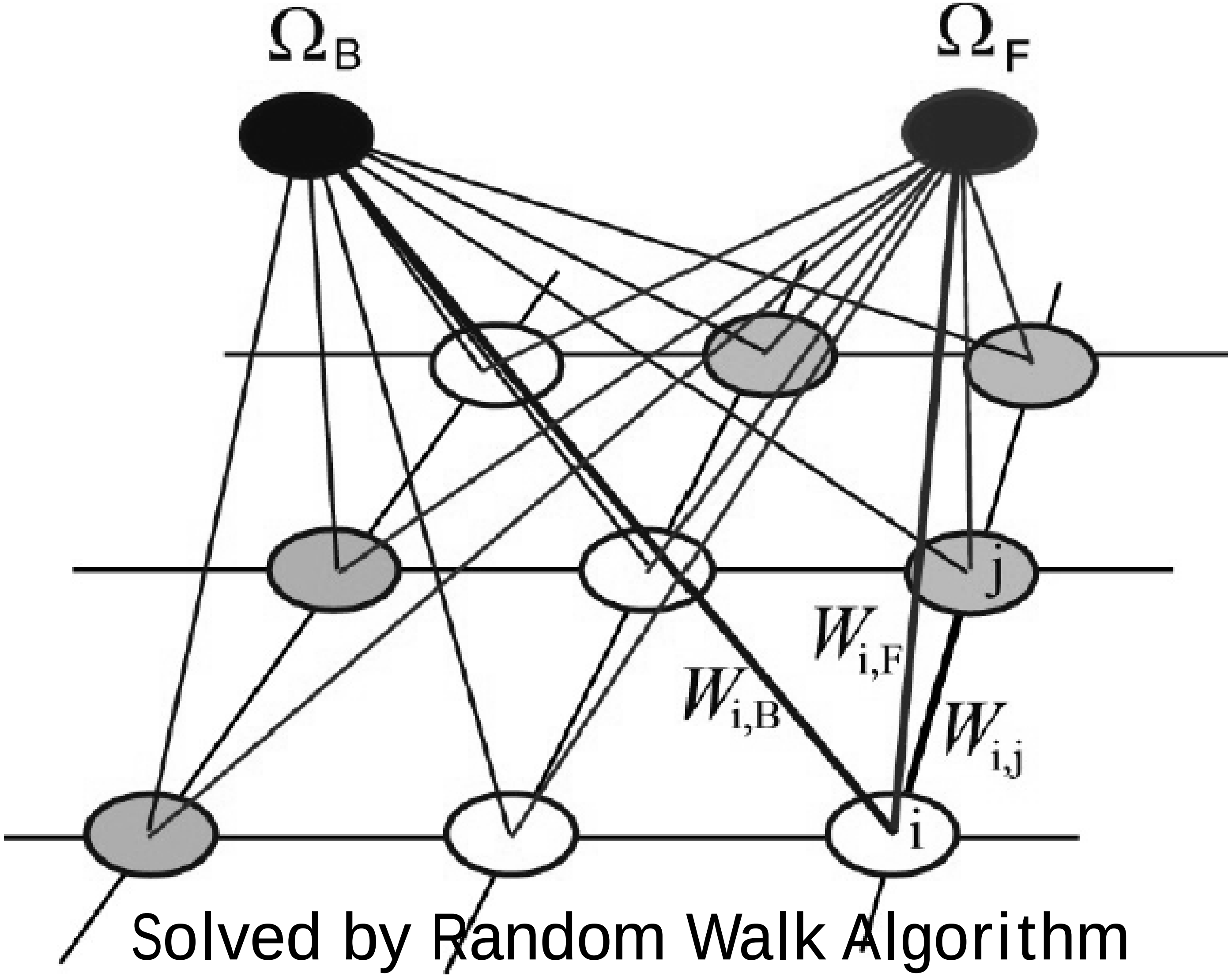


Robust matting

matte

confidence

Matte optimization



Solved by Random Walk Algorithm

Matte optimization

data constraints

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

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

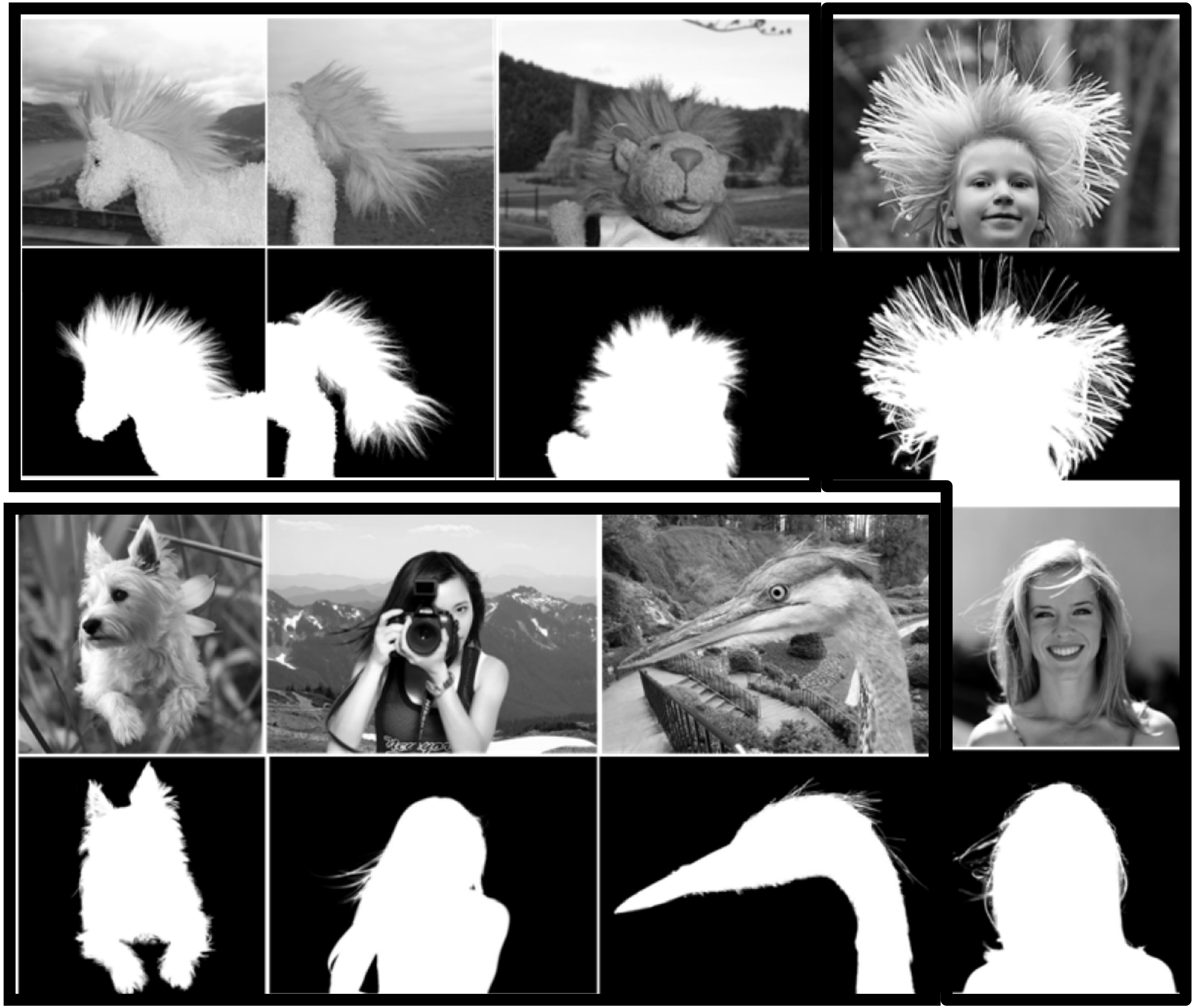
neighborhood constraints

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

Demo (EZ Mask)

Evaluation

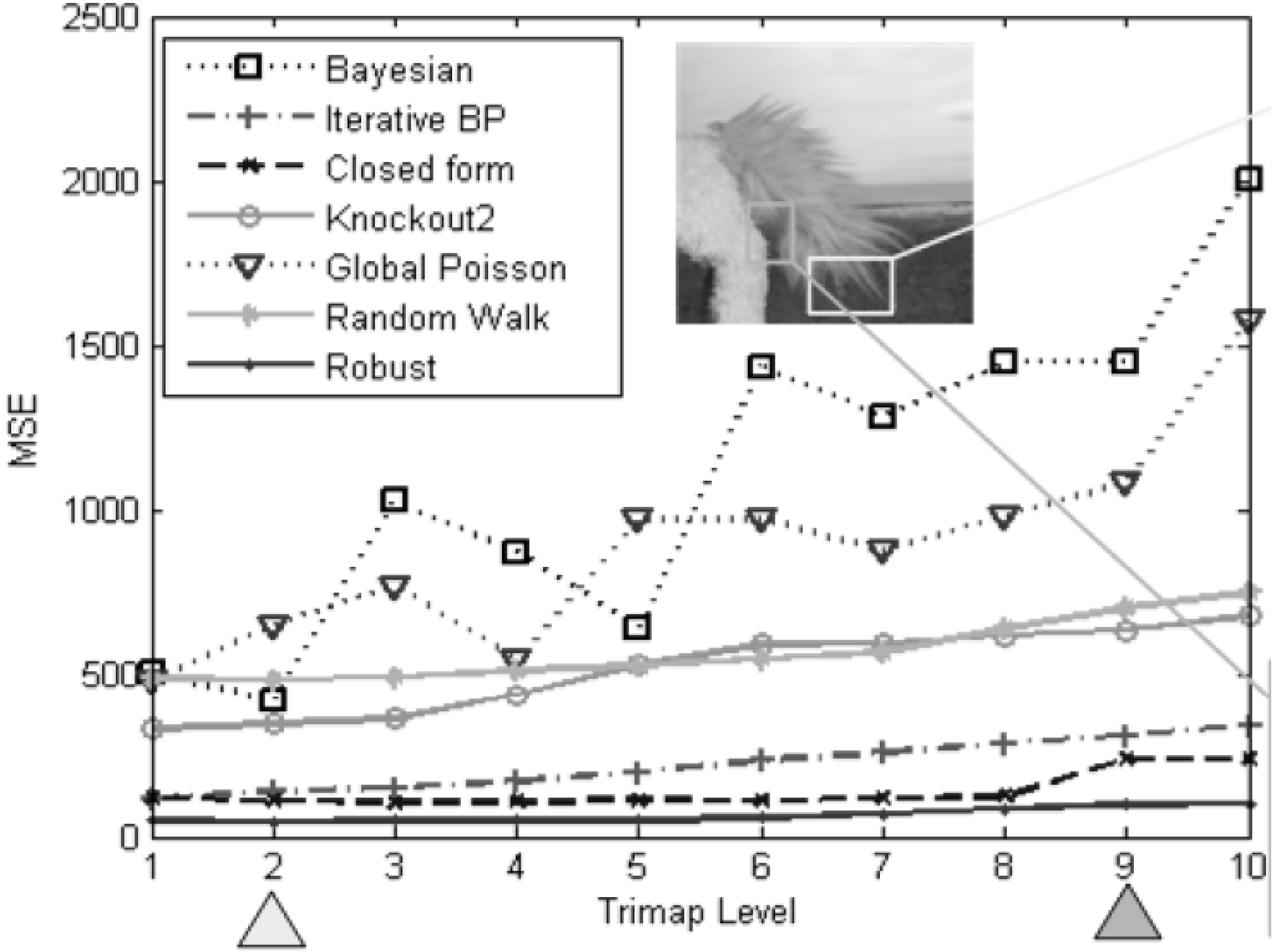
- 8 images collected in 3 different ways
- Each has a “ground truth” matte

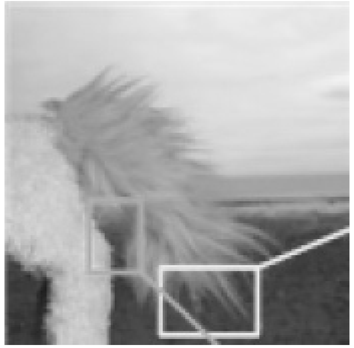


Evaluation

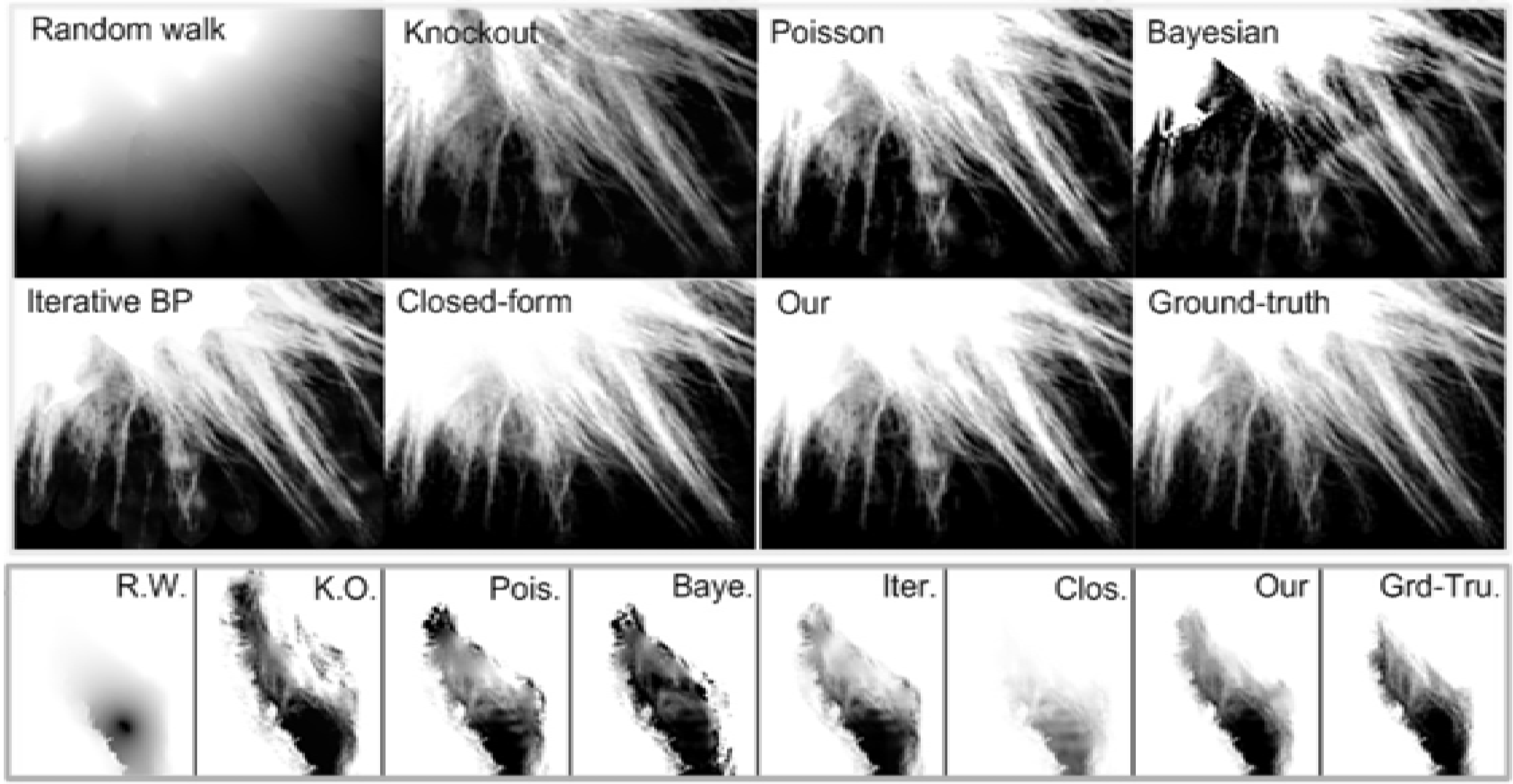
- Mean square error is used as the accuracy metric
- Try 8 trimaps with different accuracy for testing robustness
- 7 methods are tested: Bayesian, Belief propagation, Poisson, Random Walk, KnockOut2, Closed-Form and Robust matting

Quantitative evaluation

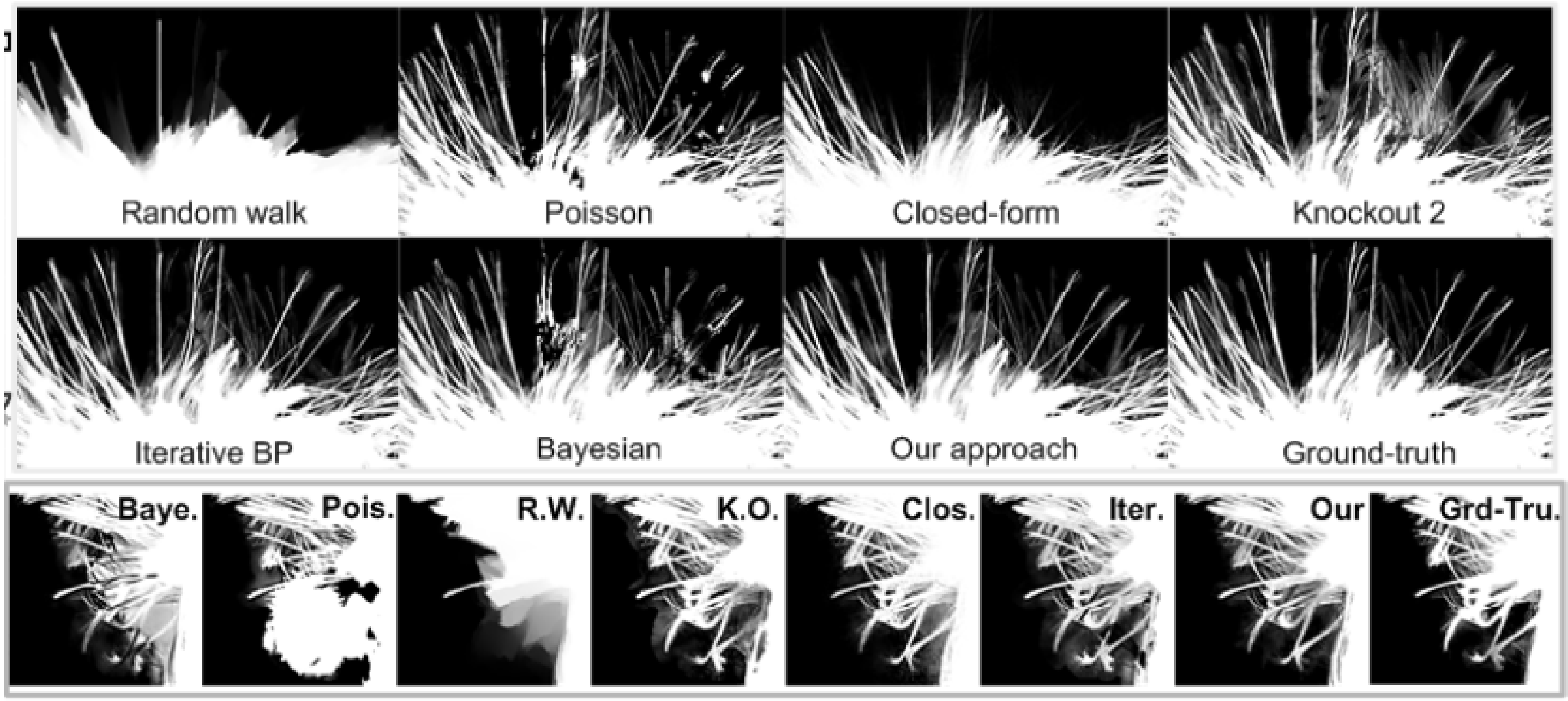




Subjective evaluation



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/

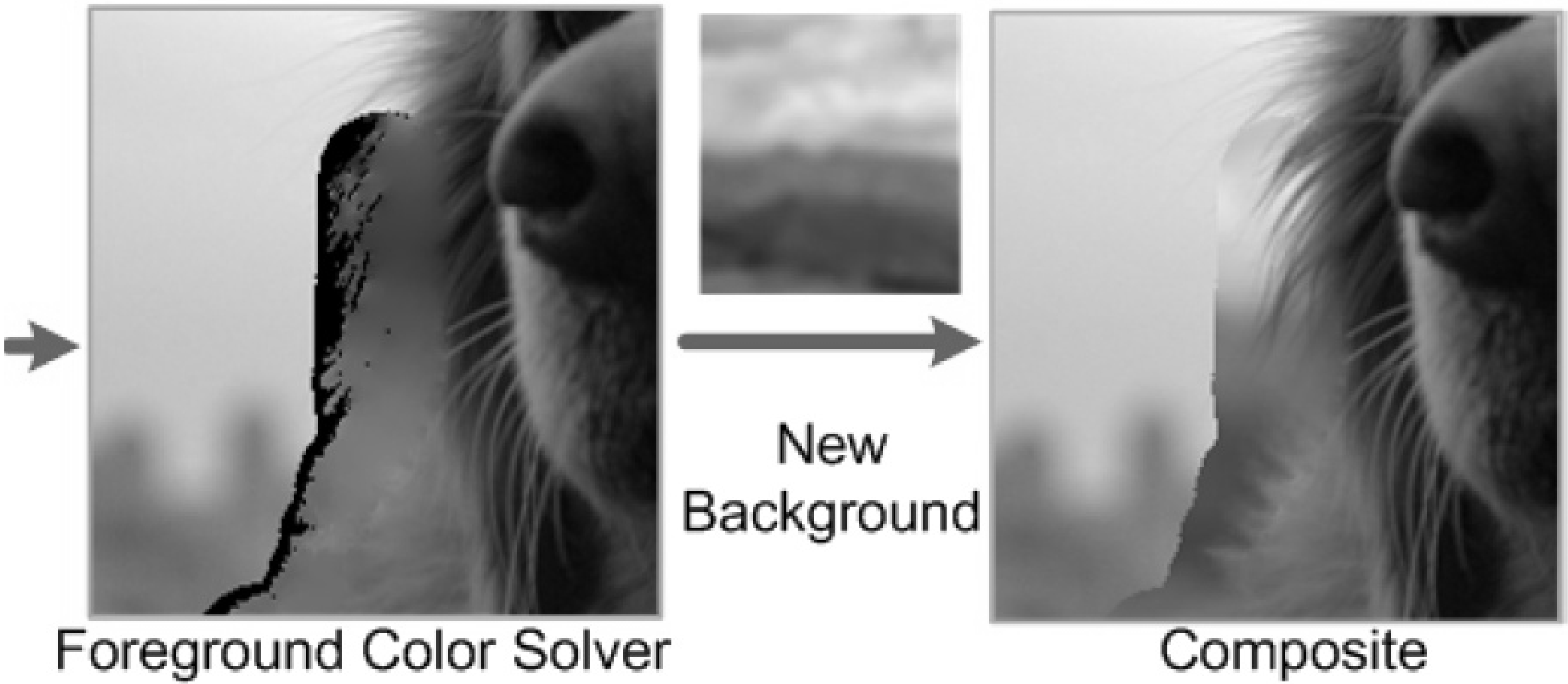
Method	SAD	MSE	Grad.	Conn.
Closed-form [13]	**1.3**	**1.4**	**1.5**	2.0
Robust matting [23]	1.9	1.8	1.7	3.4
Random walk [8]	3.3	3.2	3.5	**1.3**
Easy matting [9]	4.0	4.4	4.2	3.7
Bayesian matting [6]	4.5	4.3	4.3	5.0
Poisson matting [20]	5.9	5.9	6.0	5.6

Soft scissor

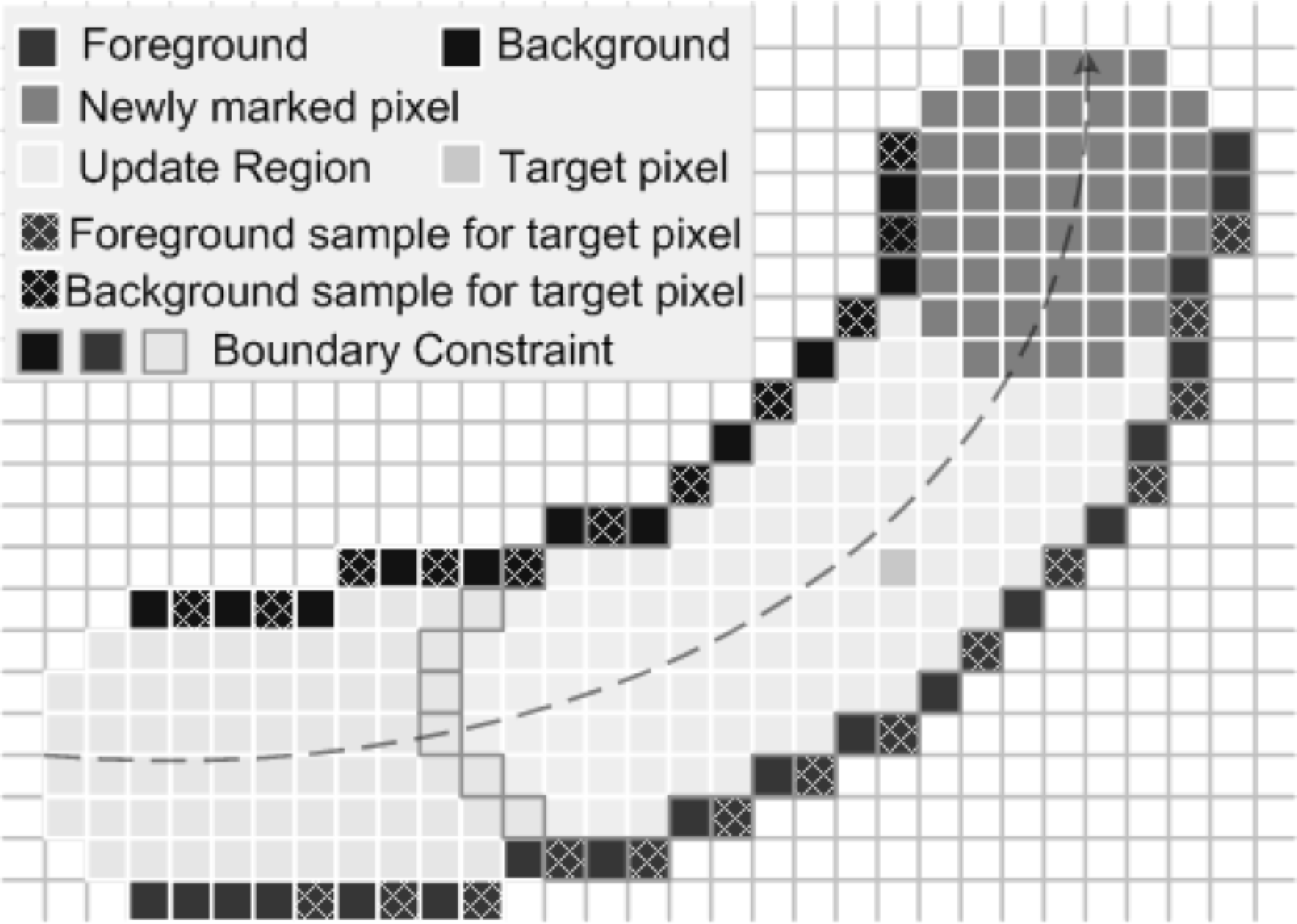
- Jue Wang et. al., SIGGRAPH 2007
- Users interact in a similar way to intelligent scissors

Flowchart

Flowchart



Soft scissor



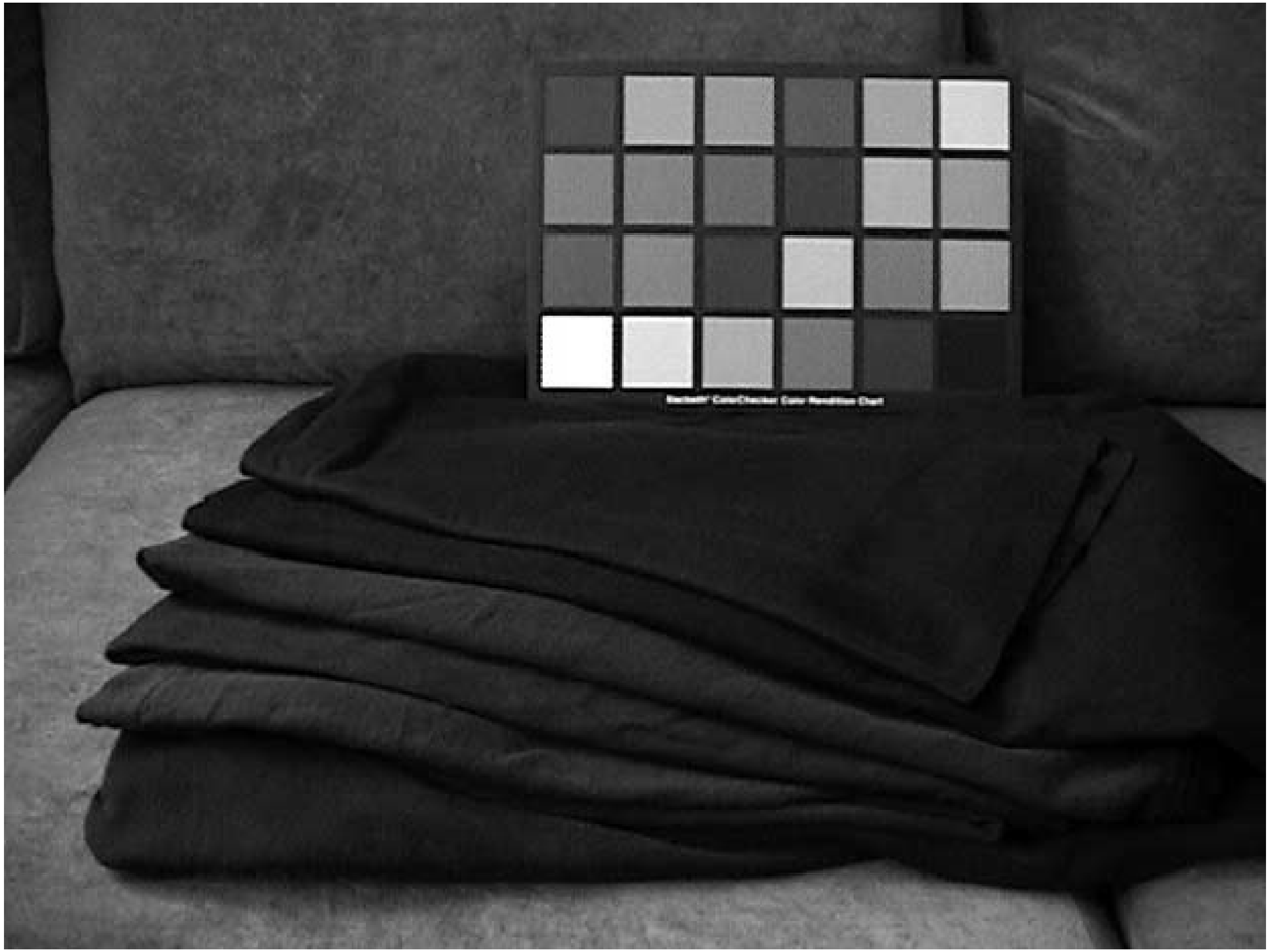
Demo (Power Mask)

Outline

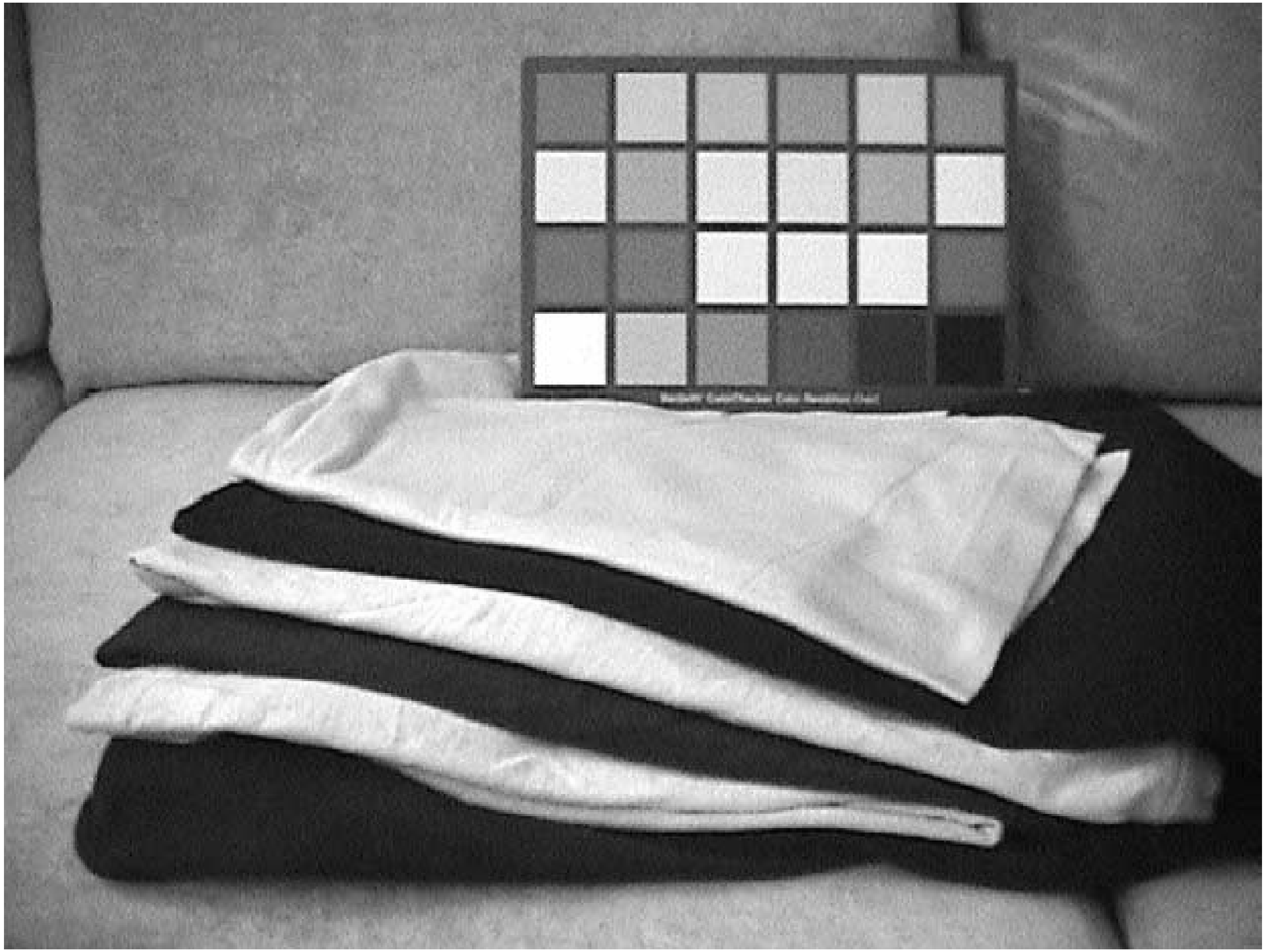
- Traditional matting and compositing
- The matting problem
- Bayesian matting and extensions
- Matting with less user inputs
- Matting with multiple observations
- Beyond the compositing equation*
- Conclusions

Matting with multiple observations

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

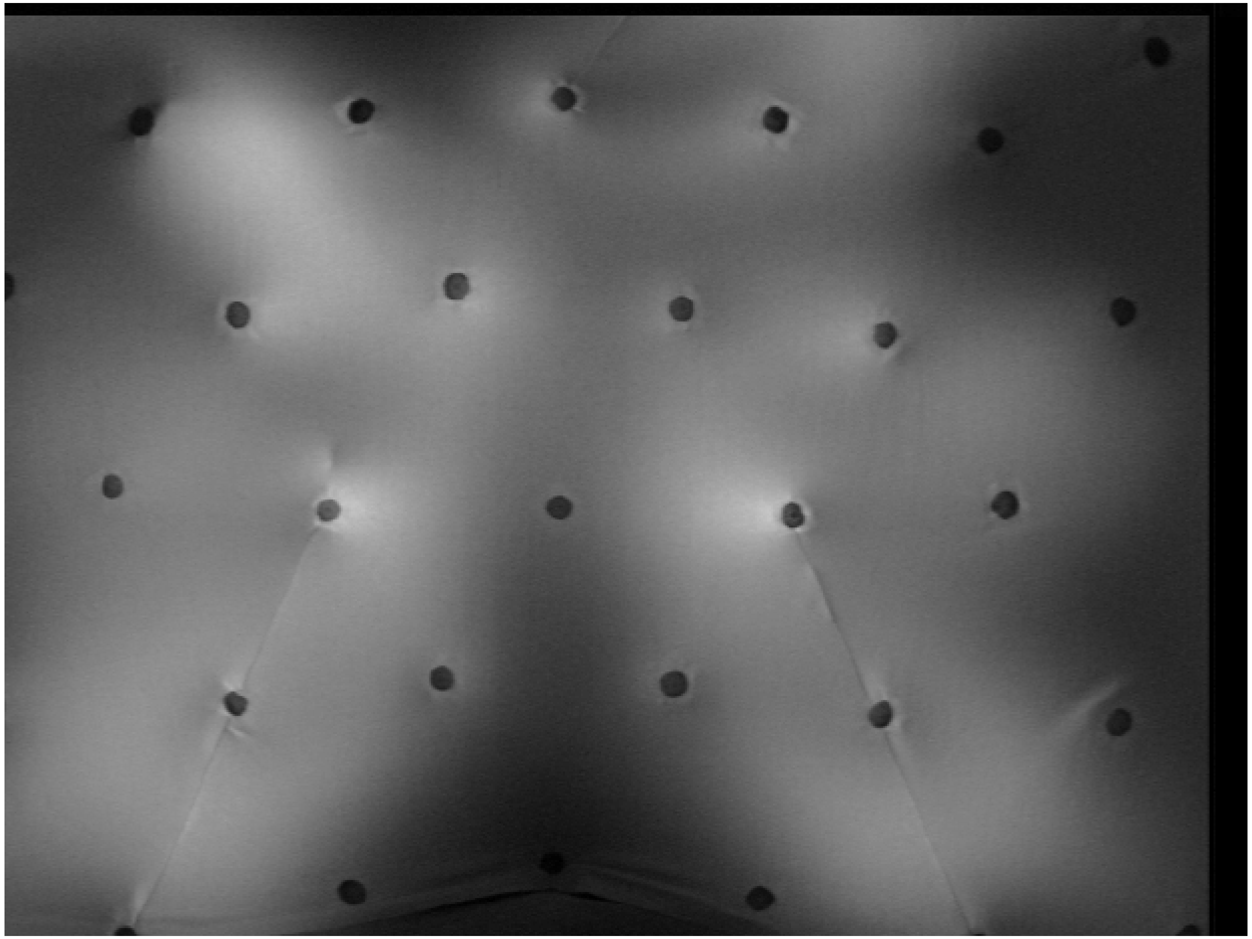


Invisible lights (Infared)



Invisible lights (Infared)

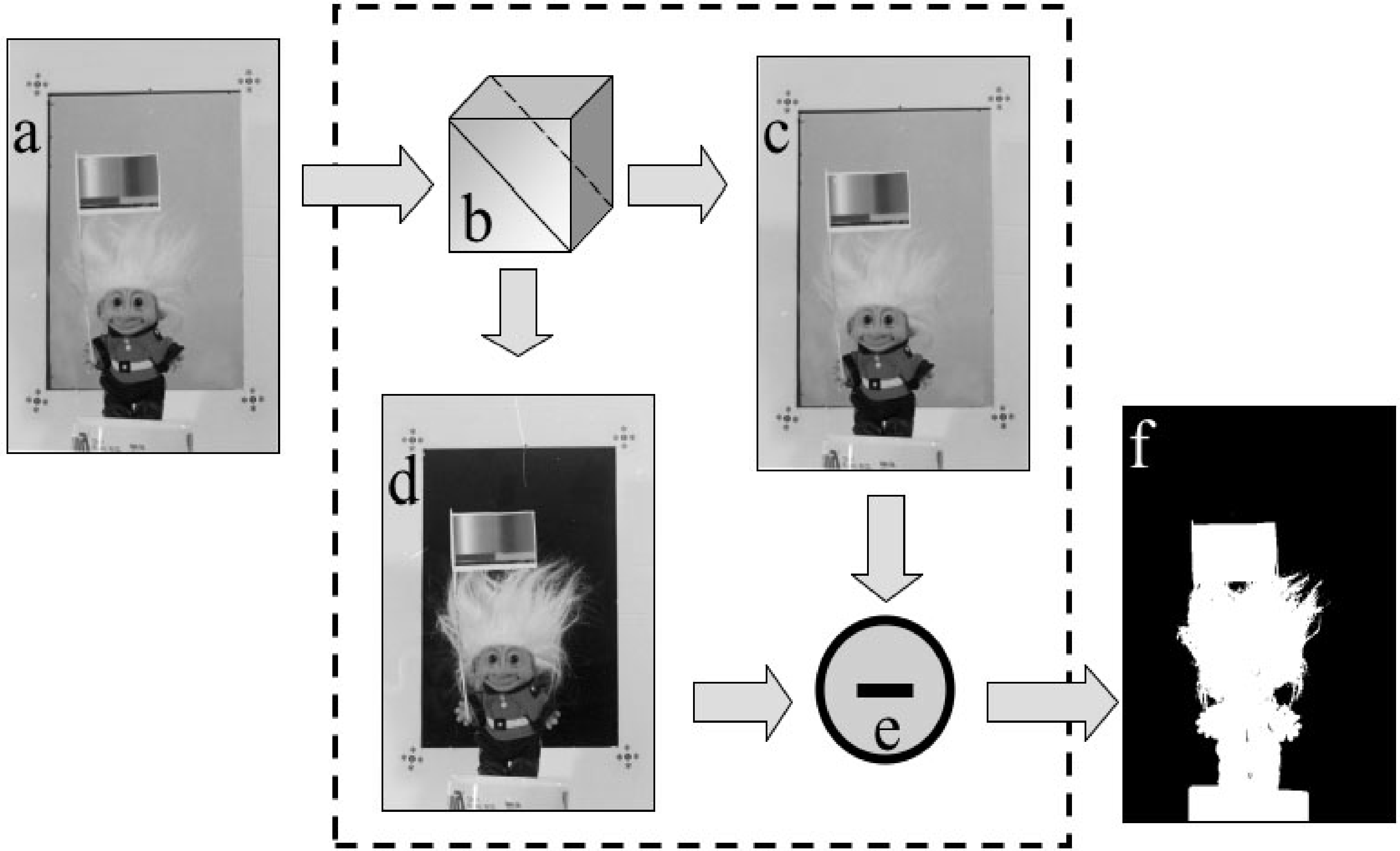
Invisible lights (Infared)



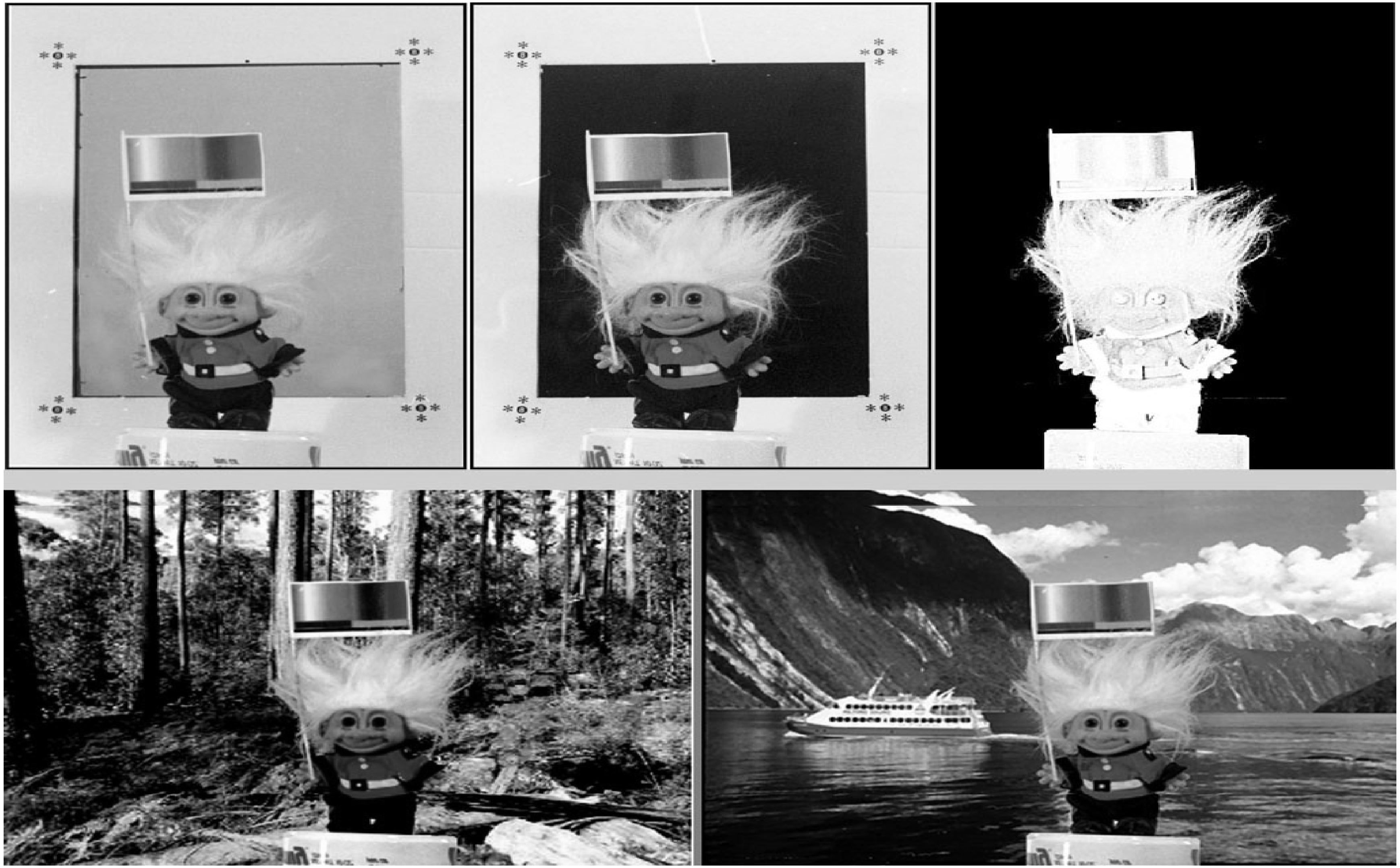
Invisible lights (Infared)

Invisible lights (Infared)

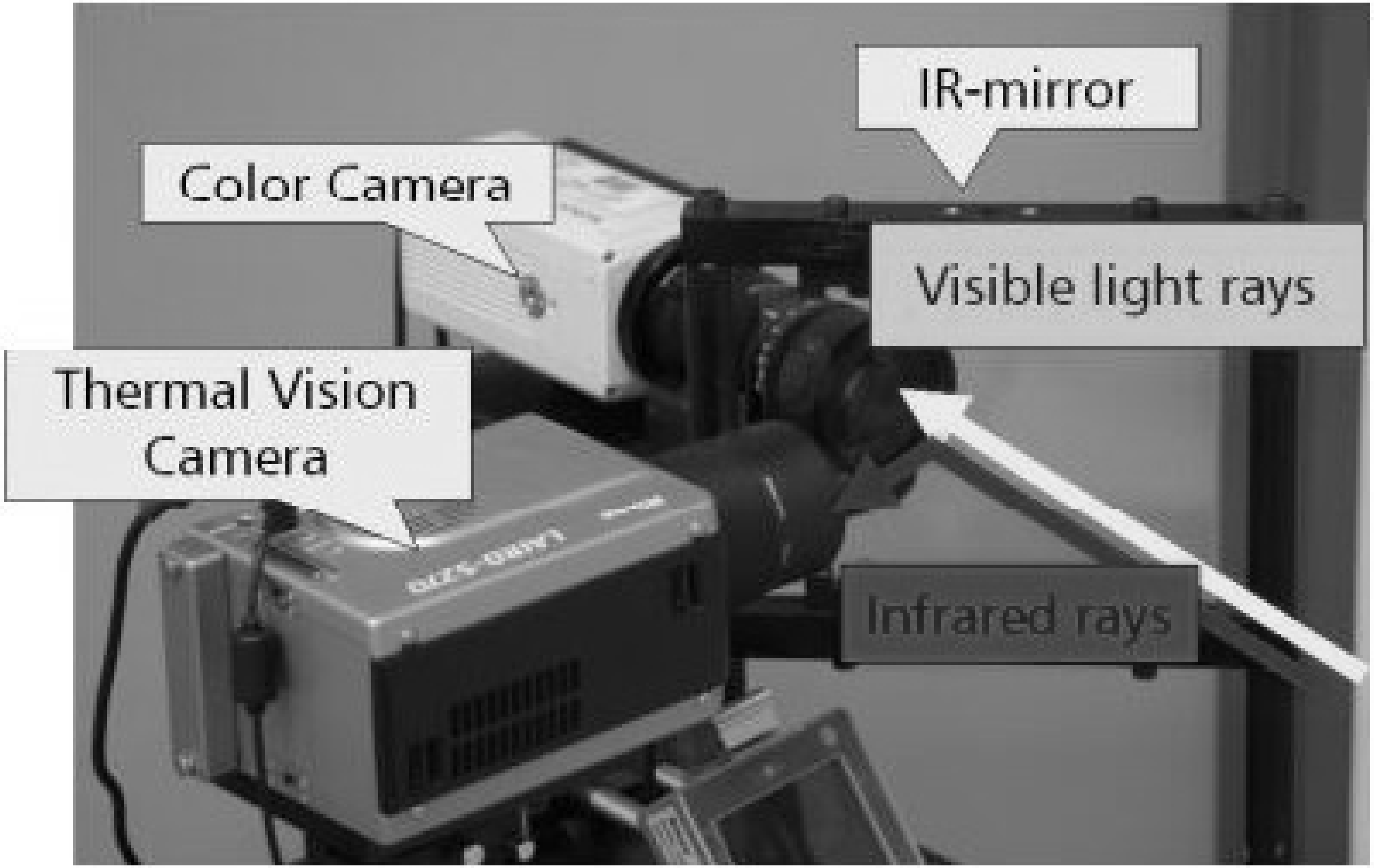
Invisible lights (Infared)



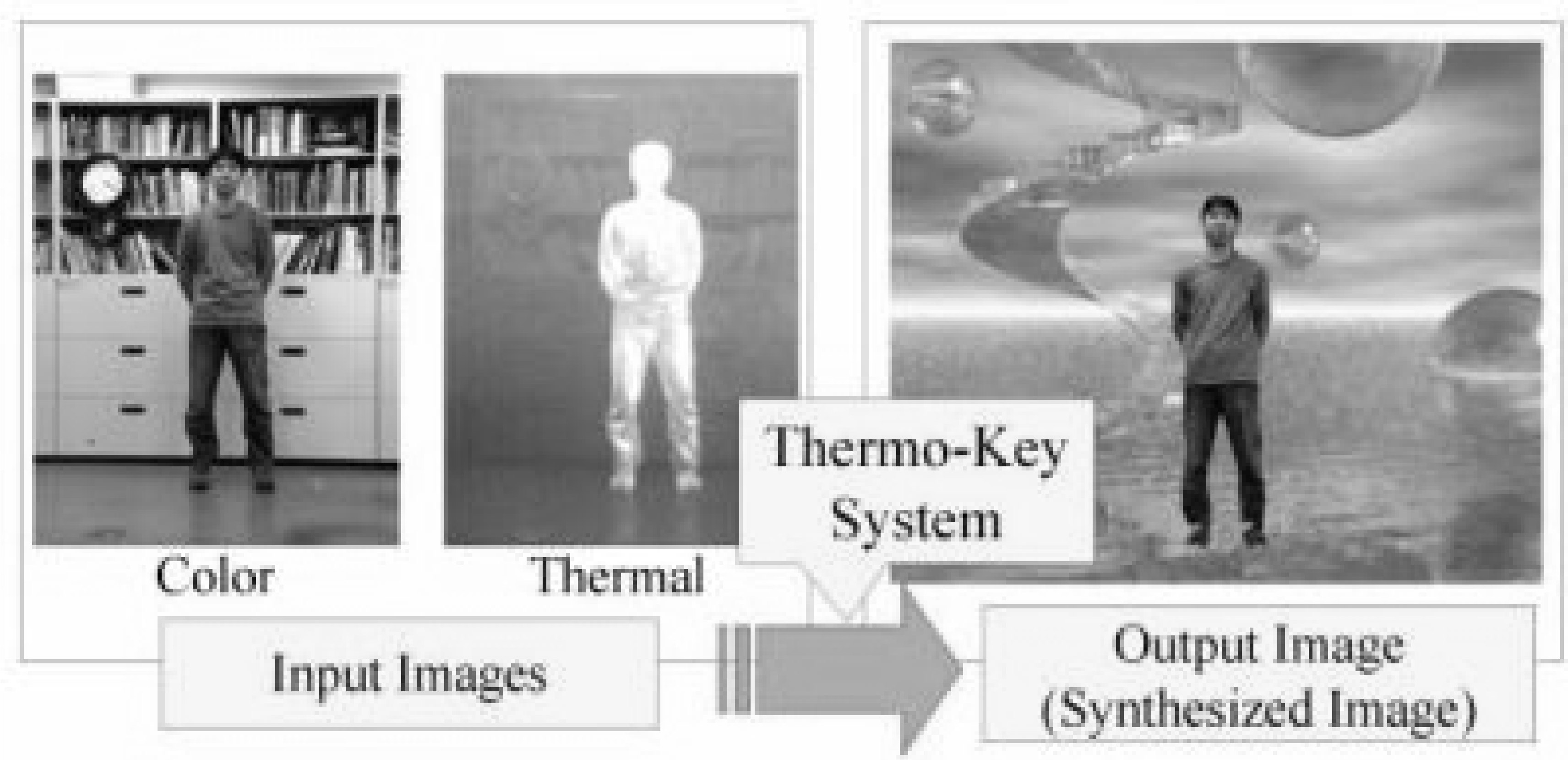
Invisible lights (Polarized)



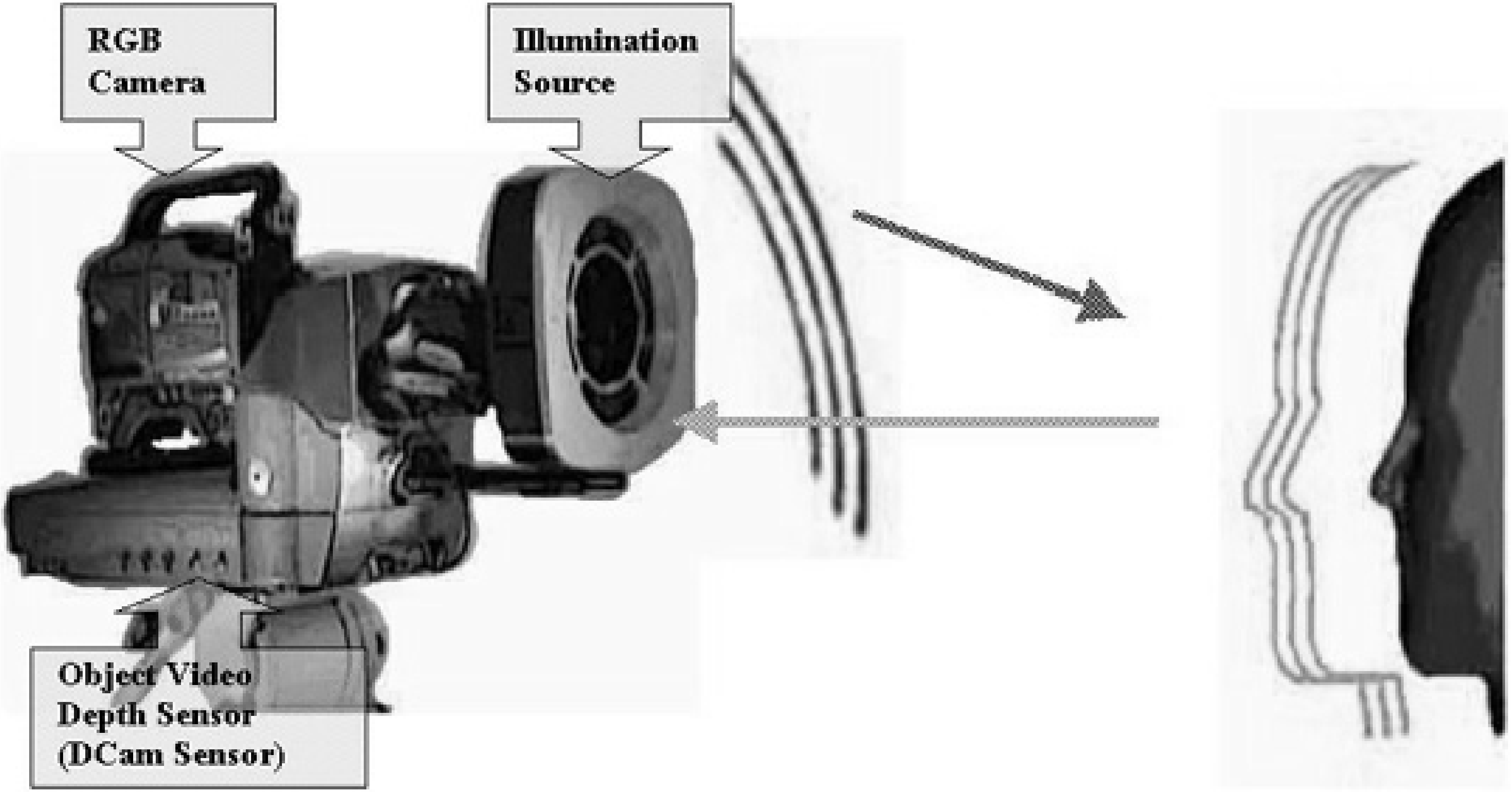
Invisible lights (Polarized)


IR-mirror
Color Camera
Visible light rays
Thermal Vision Camera
Infrared rays

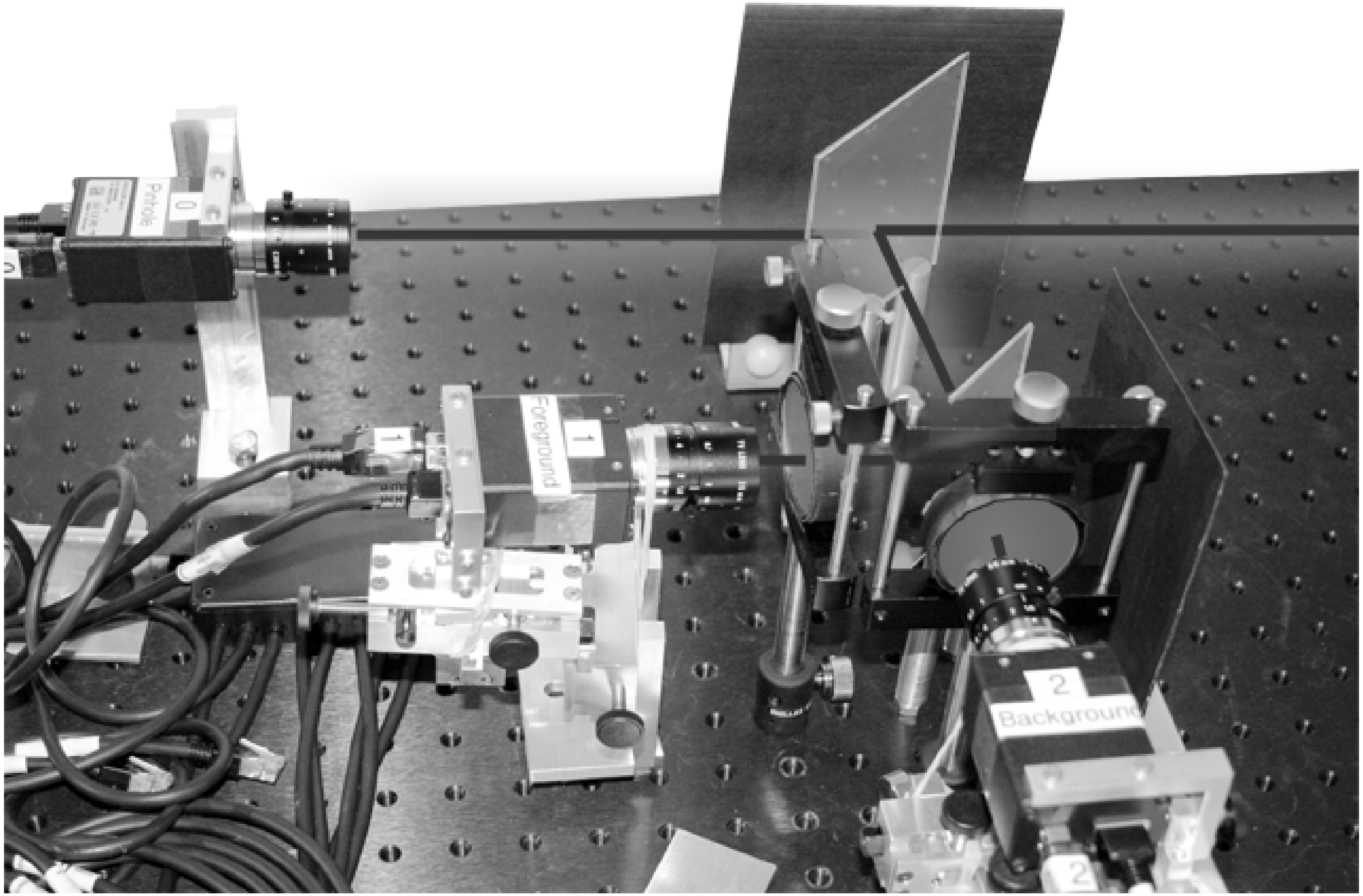
Thermo-Key


Color
Thermal
Input Images
Thermo-Key
System
Output Image
(Synthesized Image)

Thermo-Key


RGB Camera
Illumination Source
Object Video Depth Sensor (DCam Sensor)

ZCam



Defocus matting

video

video

Matting with camera arrays

flash | no flash | matte

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.

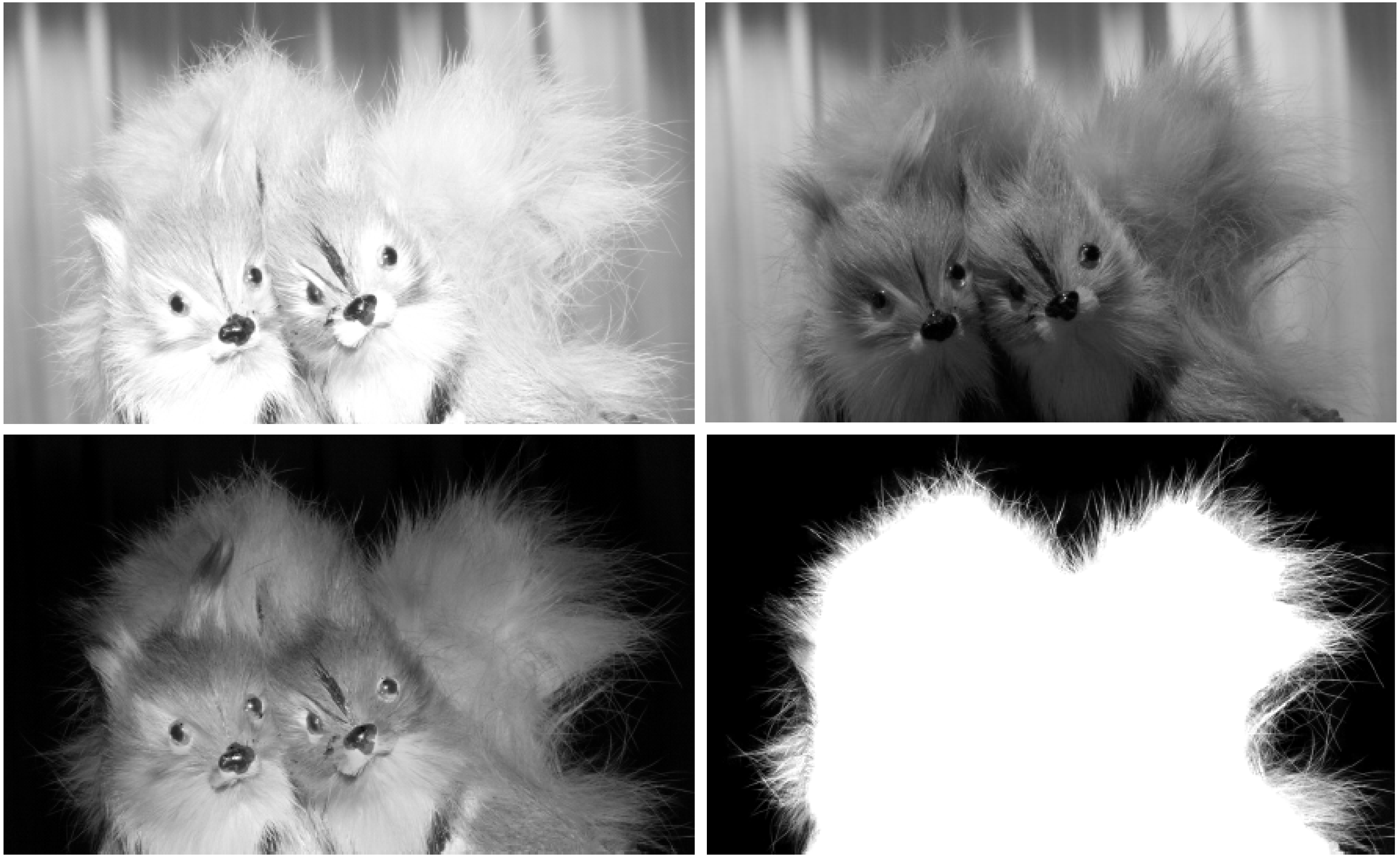
$$\arg\max_{\alpha, F'} L(\alpha, F' | I')$$

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

$$L(I'|\alpha, F') = -||I' - \alpha F'||/\sigma_{I'}^2$$

$$L(F') = -(F' - \overline{F'})^T \Sigma_{F'}^{-1} (F' - \overline{F'})$$

Flash matting



Foreground flash matting

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

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

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

flash

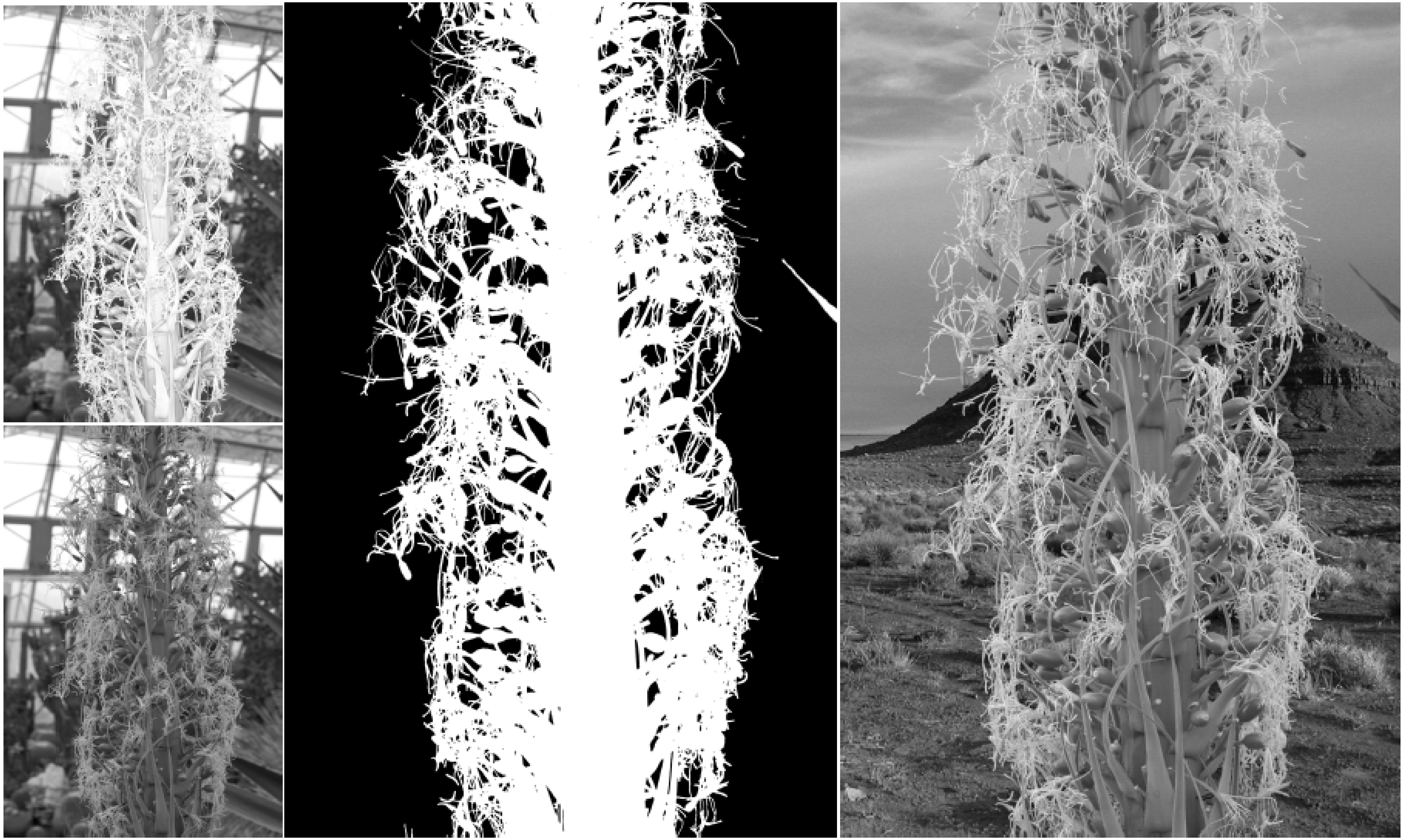
no flash

Comparison

foreground
flash matting

ioint Bayesian
flash matting

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