

# Visual Computing: Exercise Matting 2 (send in till Friday)

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IVD - Institut für Visualisierung und Datenanalyse

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# Bayesian Matting

The mean  $\mu_B$  and covariance matrix  $\Sigma_B$  can be computed from the collection of  $N_B$  background sample locations  $\{B_i\}$  in  $\mathcal{B}$  using:

$$\mu_B = \frac{1}{N_B} \sum_{i=1}^{N_B} I(B_i)$$

$$\Sigma_B = \frac{1}{N_B} \sum_{i=1}^{N_B} (I(B_i) - \mu_B)(I(B_i) - \mu_B)^\top$$
(2.14)

We can do the same thing for the foreground pixels in the trimap. Therefore, we can obtain estimates for the prior distributions in Equation (2.10) as:

$$\log P(B) \approx -(B - \mu_B)^\top \Sigma_B^{-1} (B - \mu_B)$$

$$\log P(F) \approx -(F - \mu_F)^\top \Sigma_F^{-1} (F - \mu_F)$$
(2.15)

where we've omitted constants that don't affect the optimization. For the moment, let's also assume  $P(\alpha)$  is constant (we'll relax this assumption shortly). Then sub-

numerical stability

## Citation [\(bibTex\)](#)

Yung-Yu Chuang, Brian Curless, David H. Salesin, and Richard Szeliski. A Bayesian Approach to Digital Matting. In *Proceedings of IEEE Computer Vision and Pattern Recognition (CVPR 2001)*, Vol. II, 264-271, December 2001

## Paper



[CVPR 2001 paper \(3.6MB PDF\)](#)

## Addendum

- We forgot to mention one thing in the paper. Because foreground and background samples are also observations from the camera, they should have the same noise characteristics as the observation  $C$ . Hence, we added the same amount of camera variance  $\sigma_c^2$  to the covariance matrices of foreground and background samples in Equation (7). We used eigen-analysis to find the orientation of the covariance matrix and added  $\sigma_c^2$  in every axis. That is, we decomposed  $\Sigma_F$  as  $U S V^T$ . Let  $S = \text{diag}\{s_1^2, s_2^2, s_3^2\}$ , we set  $S' = \text{diag}(s_1^2 + \sigma_c^2, s_2^2 + \sigma_c^2, s_3^2 + \sigma_c^2)$  and assign the new  $\Sigma_F$  as  $U S' V^T$ . By doing so, we also avoided most of the degenerate cases, i.e., non-invertible matrices.
- For the window for collecting foreground and background samples, we set a minimal window size and a minimal number of samples. We start from a window with the minimal window size. If such a window does not give us enough samples, we gradually increase the window until the minimal number of samples is satisfied. Note that, in this way, the windows for background and foreground might end up with different sizes.



## Results

### Inputs, Masks and Composites

Blue-screen matting



Difference matting



Natural image matting



2.4 Consider  $\alpha$  as a function of  $I_b$  and  $I_g$  in Vlahos's equation (2.4), where both color channels are in  $[0, 1]$ . Plot this surface for  $a_1 = \frac{1}{2}$  and  $a_2 = 1$ . What happens as  $a_1$  is increased for fixed  $a_2$ ? What happens as  $a_2$  is increased for fixed  $a_1$ ? Interpret your results.

2.7 A pixel is observed to have intensity  $[150, 100, 200]^T$  in front of a pure blue background, and intensity  $[140, 180, 40]^T$  in front of a pure green background. Compute  $\alpha$  using triangulation.

2.9 Suppose that the foreground and background pdfs in a matting problem are modeled as Gaussian distributions with

$$\mu_F = \begin{bmatrix} 150 \\ 150 \\ 150 \end{bmatrix} \quad \Sigma_F = \begin{bmatrix} 20 & 5 & 5 \\ 5 & 30 & 8 \\ 5 & 8 & 25 \end{bmatrix} \quad (2.88)$$

$$\mu_B = \begin{bmatrix} 50 \\ 50 \\ 200 \end{bmatrix} \quad \Sigma_B = \begin{bmatrix} 5 & 0 & 0 \\ 0 & 5 & 0 \\ 0 & 0 & 15 \end{bmatrix} \quad (2.89)$$

If the observed pixel color is  $[120, 125, 170]^\top$ , compute  $F$ ,  $B$ , and  $\alpha$  by alternating Equation (2.16) and Equation (2.17), assuming  $\sigma_d = 2$ . Repeat the experiment with  $\sigma_d = 10$  and interpret the difference.

# Closed Form Matting

- How to get F and B from alpha matte?
- Visualize Color Line Assumption for different window sizes

# Resources/ References

## A Bayesian Approach to Digital Matting

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<http://grail.cs.washington.edu/projects/digital-matting/>

## A Closed Form Solution to Natural Image Matting

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### Abstract

*Interactive digital matting, the process of extracting a foreground object from an image based on limited user input, is an important task in image and video editing. From a computer vision perspective, this task is extremely chal-*

color image, at each pixel there are 3 equations and 7 unknowns.

Obviously, this is a severely under-constrained problem, and user interaction is required to extract a good matte. Most recent methods expect the user to provide a *trimap*

- A Bayesian Approach to Digital Matting  
<http://grail.cs.washington.edu/projects/digital-matting/image-matting/>
- [CVFX] Computer Vision for Visual Effects, R. Radke, Ch. 2
- <http://www.alphamatting.com/datasets.php>



# Details

- python libraries
  - <http://scikit-image.org/>
  - <https://www.scipy.org/>
  - <http://www.numpy.org/>
  - <http://matplotlib.org/>
  - <http://opencv.org/> —> <http://simplecv.org/>
- Python tutorials:
  - <http://pythonvision.org/basic-tutorial/>
  - <https://codewords.recurse.com/issues/six/image-processing-101>

# Project