

# Lecture 20-2 Closed-form matting

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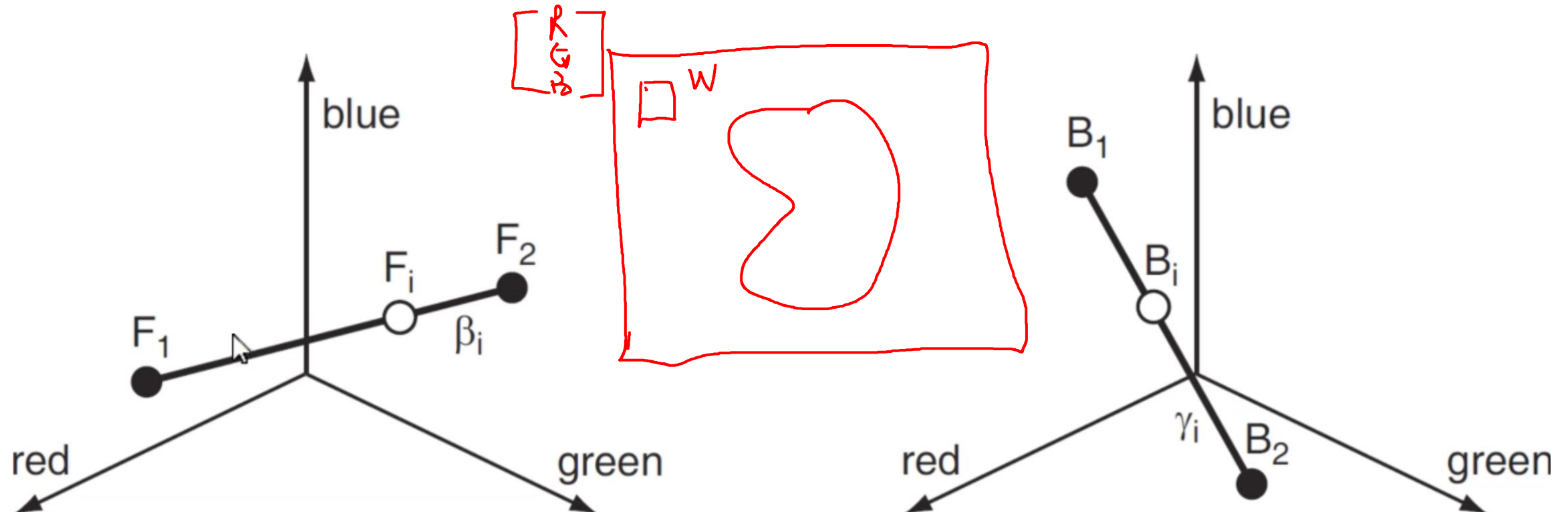
SIST Building 2 302-F/302-C

Course piazza link:

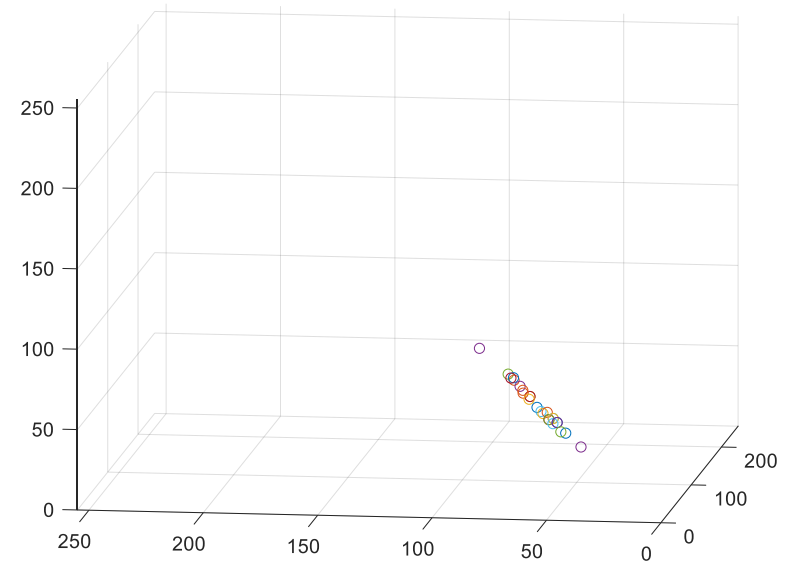
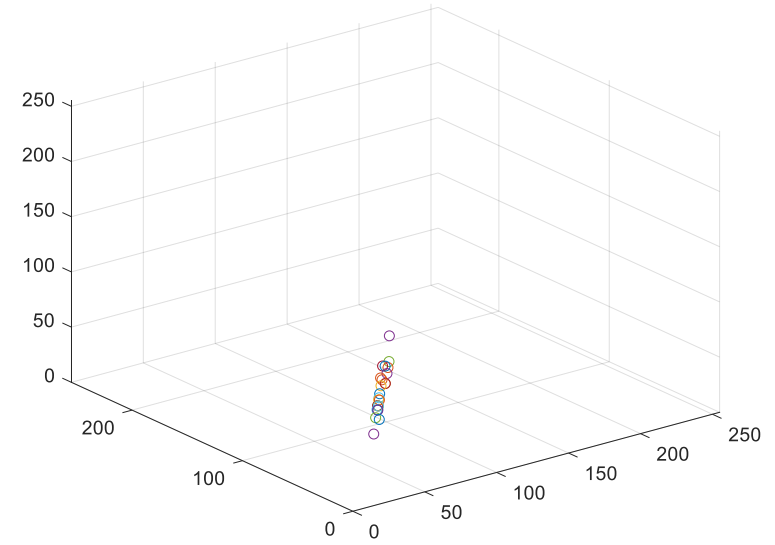
[piazza.com/shanghaitech.edu.cn/spring2021/cs270spring2021](https://piazza.com/shanghaitech.edu.cn/spring2021/cs270spring2021)

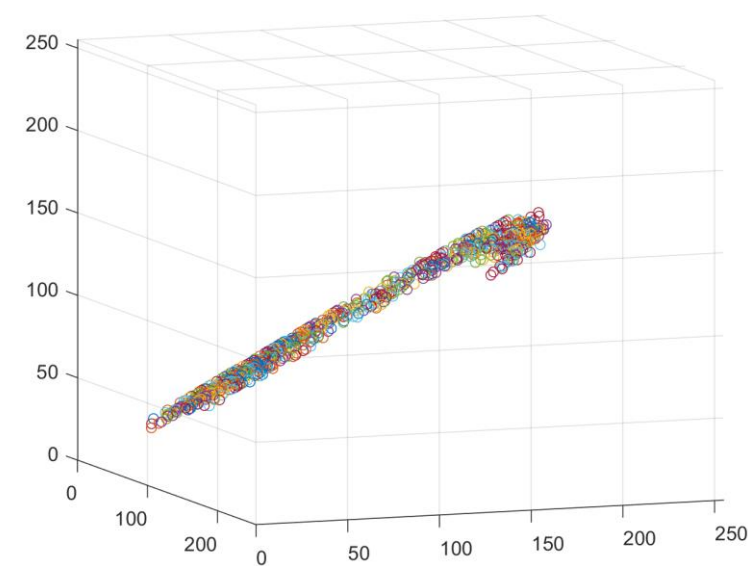
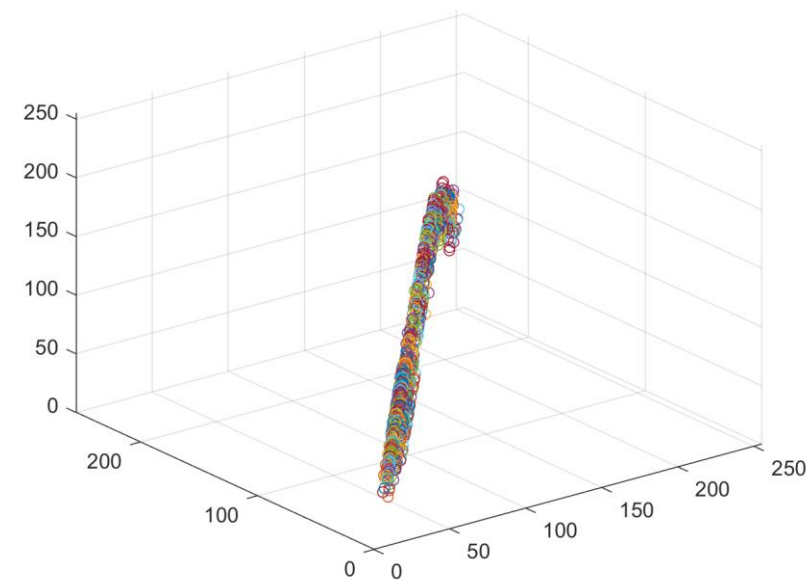
# Closed-form matting

$$I = \alpha \cdot F + [1 - \alpha] \cdot B$$



Color line assumption





# Closed-form matting

- Color line assumption:
- FG and BG colors in a small window lie on a straight line in RGB space.
- Line depends on which window we chose.

# Closed-form matting

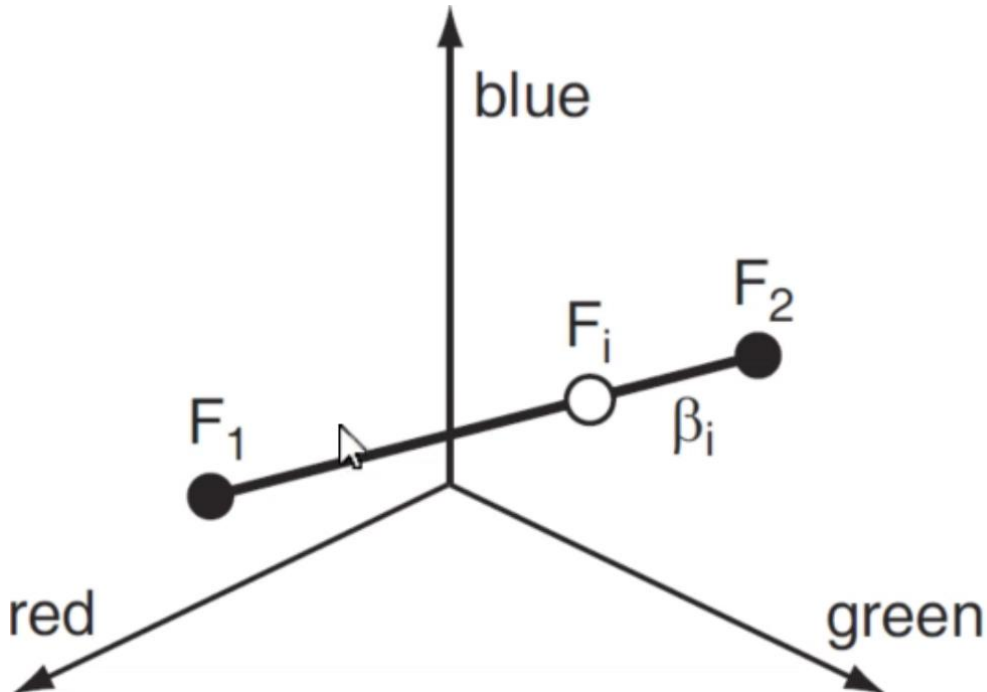
$$F_i = \beta_i F_1 + (1 - \beta_i) F_2$$

$$B_i = \gamma_i B_1 + (1 - \gamma_i) B_2$$

If color line assumption holds,  
then the true matte ( $\alpha$ ) satisfies

$$\alpha_i = a^T I_i + b$$

for all pixels in the window.



# Prove for the affine transformation

We combine the matting equation and the color line assumption and get:

# Cost function

$$J(\alpha_i, a_i, b_i) = \sum_{j=1}^N \sum_{i \in \text{window } j} (\alpha_i - (a_j^T I_i + b_j))^2$$

- $i$  is the index of every pixel
- $j$  is the index of every window
- For every pixel, we need to determine  $\alpha_i$
- For every window, we need to determine  $a_j$  &  $b_j$



# Cost function

There exists a tight constrain between what happen on each pixel.

$$\arg \min J(\alpha_i, a_i, b_i) = \sum_{j=1}^N \sum_{i \in \text{window } j} (\alpha_i - (a_j^T I_i + b_j))^2$$

# A relaxation for optimization

$$\sum_{j=1}^N \left\| G_j \begin{bmatrix} a_j \\ b_j \end{bmatrix} - \alpha_j \right\|^2$$

Minimizing each of these equations is a linear least square problem.

Suppose we knew the  $\alpha$ 's and the  $a$ & $b$  that make  $\left\| G_j \begin{bmatrix} a_j \\ b_j \end{bmatrix} - \alpha_j \right\|^2$  as small as possible are:

$$\begin{bmatrix} a_j \\ b_j \end{bmatrix}^* = (G_j^T G_j)^{-1} G_j^T \alpha_j$$

Then we have  $a$ & $b$  are functions of  $\alpha$ !

# Matting Laplacian

- So the whole optimization is a function of only  $\alpha$ .

$$\arg \min J(\alpha_i, a_i, b_i) = \sum_{j=1}^N \sum_{i \in \text{window } j} (\alpha_i - (a_j^T I_i + b_j))^2$$

$$\arg \min J(\alpha_j) = \sum_{j=1}^N \|G_j(G_j^T G_j)G_j^T \alpha_j - \alpha_j\|^2$$

$$\begin{aligned} &= [\alpha_1 \quad \cdots \quad \alpha_N] L \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_N \end{bmatrix} \\ &= \alpha^T L \alpha \end{aligned}$$

# Solution

$$\arg \min J(\alpha) = \alpha^T L \alpha$$

$$\frac{d}{d\alpha} = 2L\alpha = 0$$

$$L\alpha = 0$$

- Null vectors of  $L$  solves matting equation.
- Bad news: many 0-eigenvectors
- To constrain the matte, we need user input (scribbles).
- i.e. some pixels are forced to have  $\alpha = 0$  for BG and  $\alpha = 1$  for FG.

# Solution

- So we actually solve:

$$\arg \min \alpha^T L \alpha + \lambda \left( \sum_{i \in FG} (1 - \alpha_i) + \sum_{i \in BG} \alpha_i \right)^2$$

- We seek  $\alpha$ 's eigenvectors of  $L$  with eigenvalue 0 (null vectors).
- There are many such eigenvectors. And the matte we look for is a linear combination of these eigenvectors since:

if  $Lv = 0$ , and  $w = \beta_1 v_1 + \beta_2 v_2 + \dots + \beta_k v_k$

Then  $Lw = 0$

# Solution

- Idea: we have 100 grayscale eigenvectors, we can combine them to build the binary matte.
- This is called “spectral matting”.
- Cost function:

$$\min J(\alpha) = \min \sum_{i,k} |1 - \alpha_i^k|^\gamma + |\alpha_i^k|^\gamma$$
$$\alpha^k = E \beta^k$$



# Other application

$$I = Jt + (1 - t)A$$





# Take home message

- [Bayesian image matting](#)
- [Closed-form image matting](#)
- <http://people.csail.mit.edu/alevin/papers/Matting-Levin-Lischinski-Weiss-PAMI-o.pdf>
- <https://arxiv.org/pdf/2004.00626v2.pdf>
- <https://grail.cs.washington.edu/projects/background-matting/>