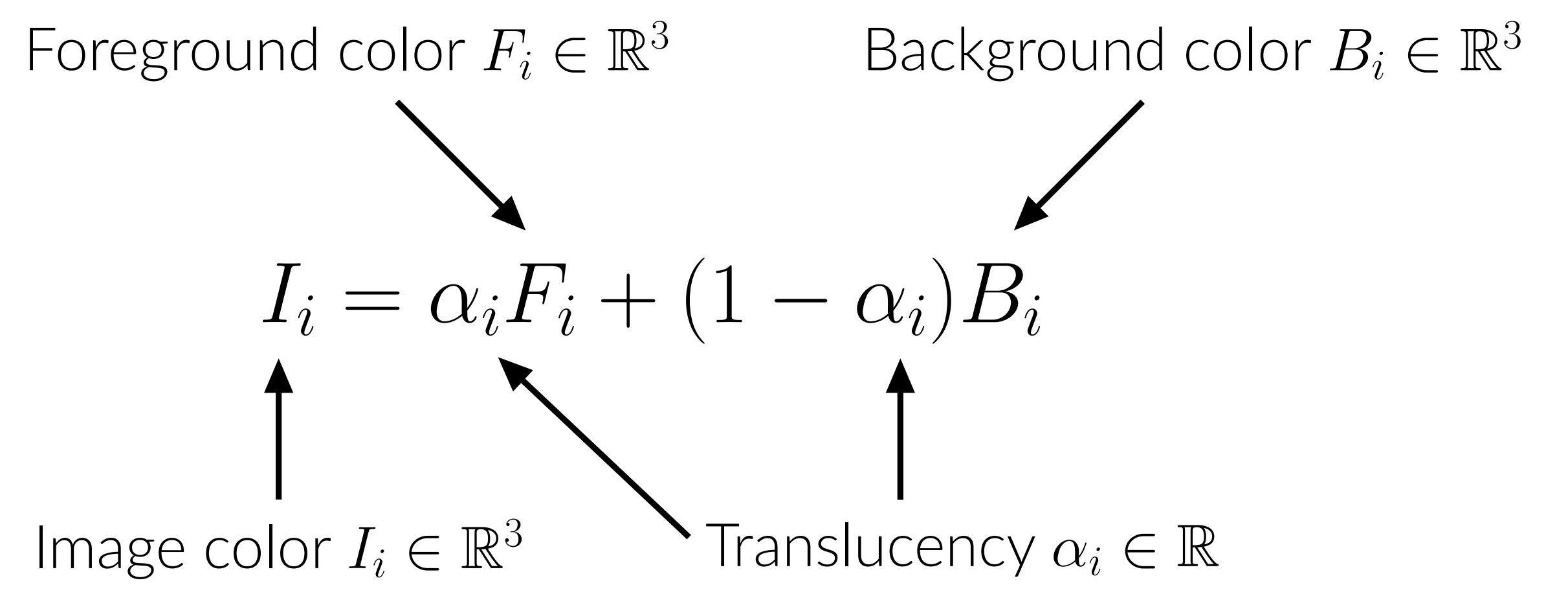
Fast Multi-Level Foreground Estimation

Thomas Germer, Tobias Uelwer, Stefan Conrad, Stefan Harmeling

Heinrich Heine University Düsseldorf, Germany

1. Compositing Equation


Foreground color $F_i \in \mathbb{R}^3$

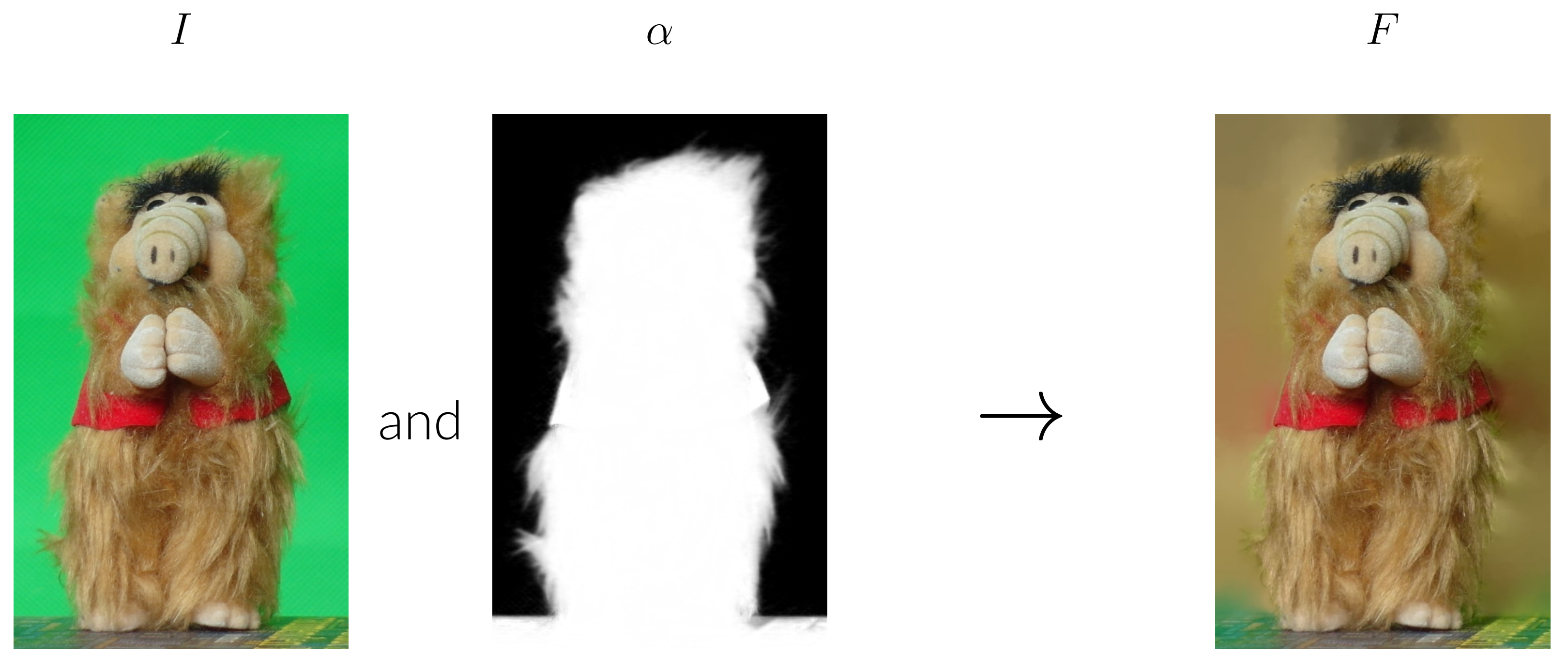
Background color $B_i \in \mathbb{R}^3$

$$I_i = \alpha_i F_i + (1 - \alpha_i) B_i$$

Image color $I_i \in \mathbb{R}^3$

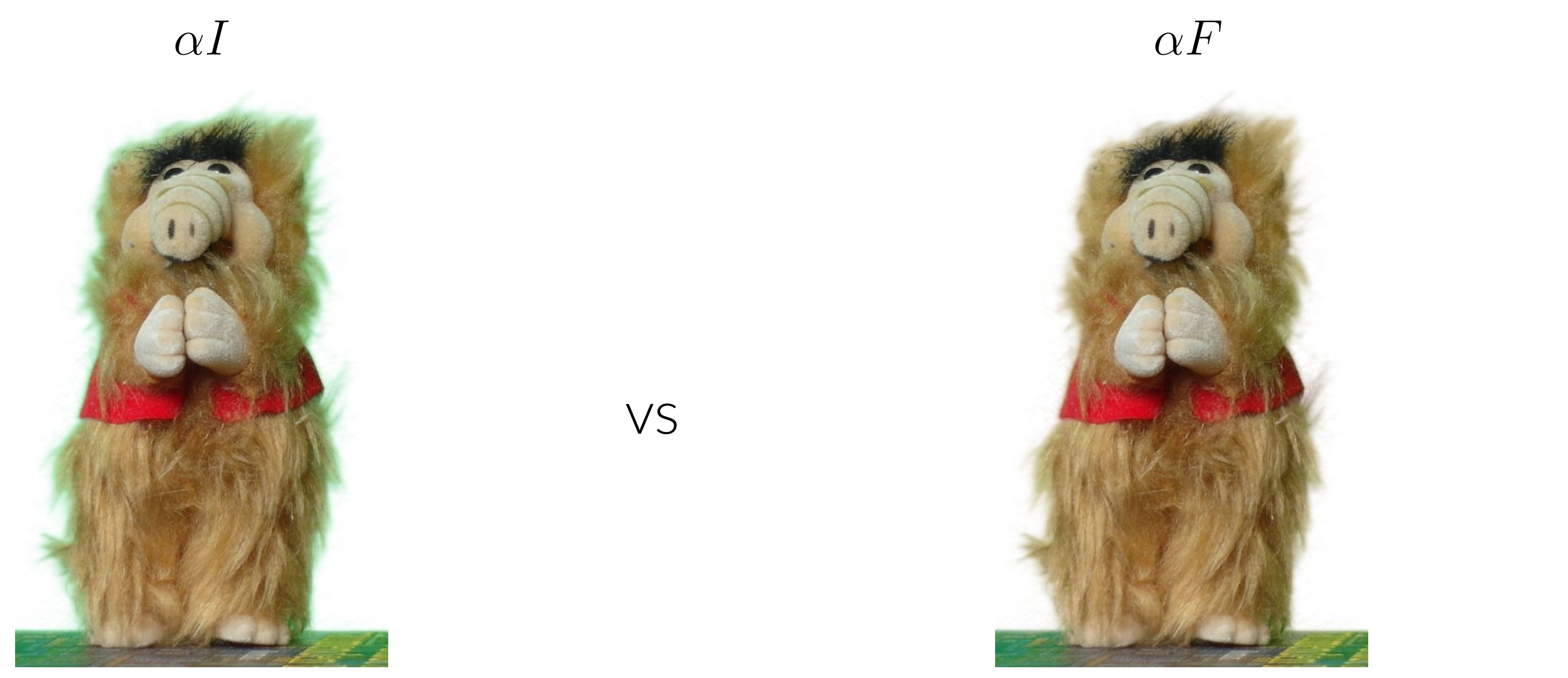
Translucency $\alpha_i \in \mathbb{R}$

2. Foreground Estimation



- **Goal:** Obtain foreground image F from image I and alpha matte α
- **Problem:** Underconstrained
  - 6 unknowns in F_i and B_i, but only 3 equations (one per color channel)

3. Motivation



Naive: Color bleeding

Solution: Estimate foreground F

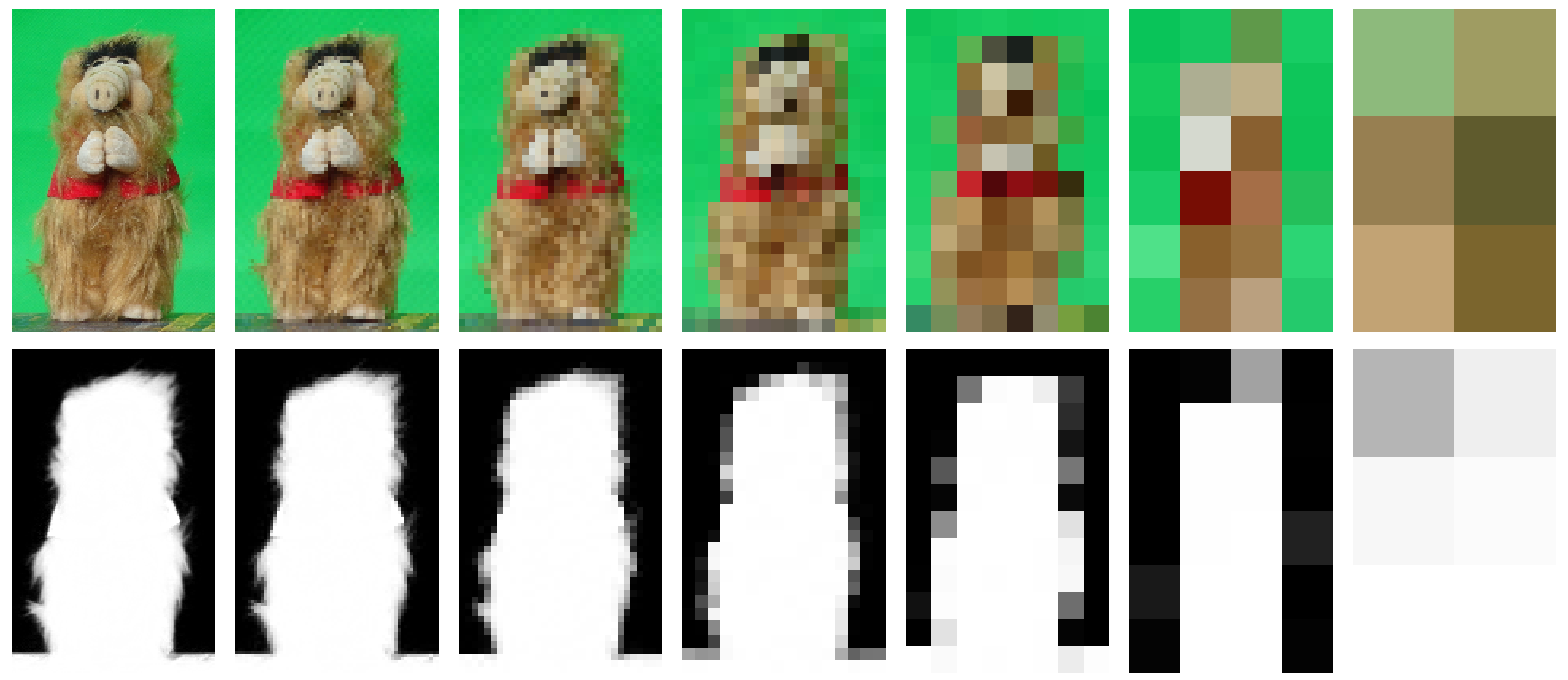
- Naively composing image I onto white background leads to color bleeding
  - $\alpha I = \alpha(\alpha F + (1-\alpha)B) = \alpha^2 F + \alpha(1-\alpha)B \neq \alpha F$

4. Our Method

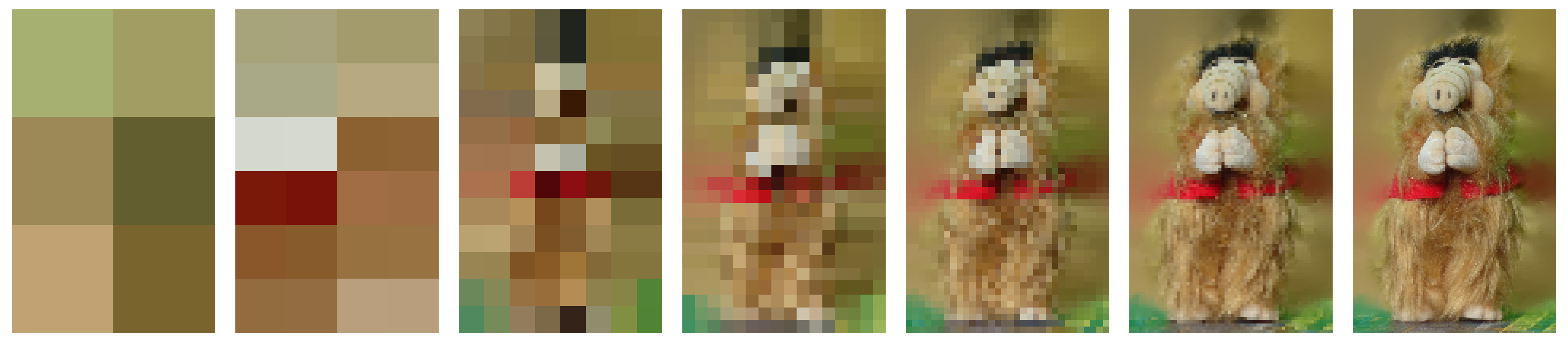
- Reformulate global cost function by [LLW07] as local cost function over neighbors $j \in N_i$

$$\text{cost}(F_i^c, B_i^c) = \overbrace{(\alpha_i F_i^c + (1-\alpha_i) B_i^c - I_i^c)^2}^{\text{Constrain composite color}} + \underbrace{\sum_{j \in N_i} (\epsilon_r + \omega |\alpha_i - \alpha_j|) \left[(F_i^c - F_j^c)^2 + (B_i^c - B_j^c)^2 \right]}_{\substack{\text{Penalize color gradients in regions of large alpha gradients} \\ \text{control regularization with parameter } \epsilon_r \\ \text{weight gradient term with parameter } \omega}}$$

- **Problem:** Iterative approach infeasible, solution only propagates slowly across image
- **Solution: Multi-level approach**
  1. Downsample input image and α until small



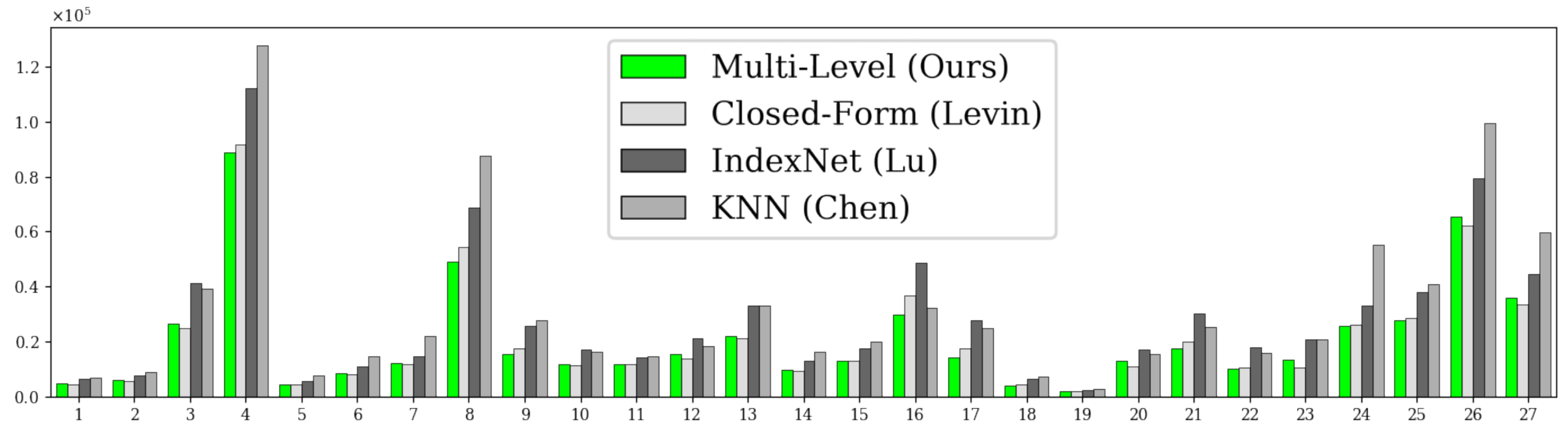
  2. Solve at lowest resolution, use upsampled result as initialization for larger size



5. Average Runtime per Image

Setup	Method	Time [s]	Std. dev. [s]
HPC	Multi-Level (Ours)	**2.04**	0.296
	Closed-Form [LLW07]	26.3	5.48
	IndexNet [LDSX19]	74.5	10.1
	KNN [CLT13]	38.2	6.47
Mac	Multi-Level (Ours)	**1.48**	0.251
	Closed-form [LLW07]	27.9	7.93
	IndexNet [LDSX19]	–	–
	KNN [CLT13]	148.0	56.2

6. Quality of Estimated Foreground



- Sum of absolute differences (SAD) for 27 images in dataset by [RRW+09]
- IndexNet [LDSX19] adapted for foreground estimation instead of alpha matting

7. Memory Usage

Method	Memory [MB]	Data Type
Multi-Level (Ours)	**1 182**	64-bit float
Closed-Form [LLW07]	7 781	64-bit float
IndexNet [LDSX19]	91 648	32-bit float
KNN [CLT13]	7 850	64-bit float

8. Open Source Implementation

- `https://github.com/pymatting/pymatting` [GUCH20]
- Easy installation via `pip install PyMatting`

```
from pymatting import *
image = load_image("image.png", "RGB")
alpha = load_image("alpha.png", "GRAY")
# Estimate foreground
foreground = estimate_foreground_ml(image, alpha)
# Concatenate RGB and alpha channels
foreground_with_alpha = stack_images(foreground, alpha)
save_image("result.png", foreground_with_alpha)
```

9. References

[CLT13] Qifeng Chen, Dingzeyu Li, and Chi-Keung Tang. KNN matting. *IEEE transactions on pattern analysis and machine intelligence*, 35(9):2175–2188, 2013.

[GUCH20] Thomas Germer, Tobias Uelwer, Stefan Conrad, and Stefan Harmeling. Pymatting: A python library for alpha matting. *Journal of Open Source Software*, 5(54):2481, 2020.

[LDSX19] Hao Lu, Yutong Dai, Chunhua Shen, and Songcen Xu. Indices matter: Learning to index for deep image matting. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 3266–3275, 2019.

[LLW07] Anat Levin, Dani Lischinski, and Yair Weiss. A closed-form solution to natural image matting. *IEEE transactions on pattern analysis and machine intelligence*, 30(2):228–242, 2007.

[RRW+09] Christoph Rhemann, Carsten Rother, Jue Wang, Margrit Gelautz, Pushmeet Kohli, and Pamela Rott. A perceptually motivated online benchmark for image matting. In *2009 IEEE Conference on Computer Vision and Pattern Recognition*, pages 1826–1833. IEEE, 2009.

`https://www.icpr2020.it/` ICPR2020 Milan 25th International Conference on Pattern Recognition `https://github.com/pymatting/pymatting`