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Opacity spatial smoothness (**Laplacian**)

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Shrink compositing paths' solution space

$$\|\text{original} - \text{reconstructed image}\|^2 \text{ (\textbf{polynomial})}$$

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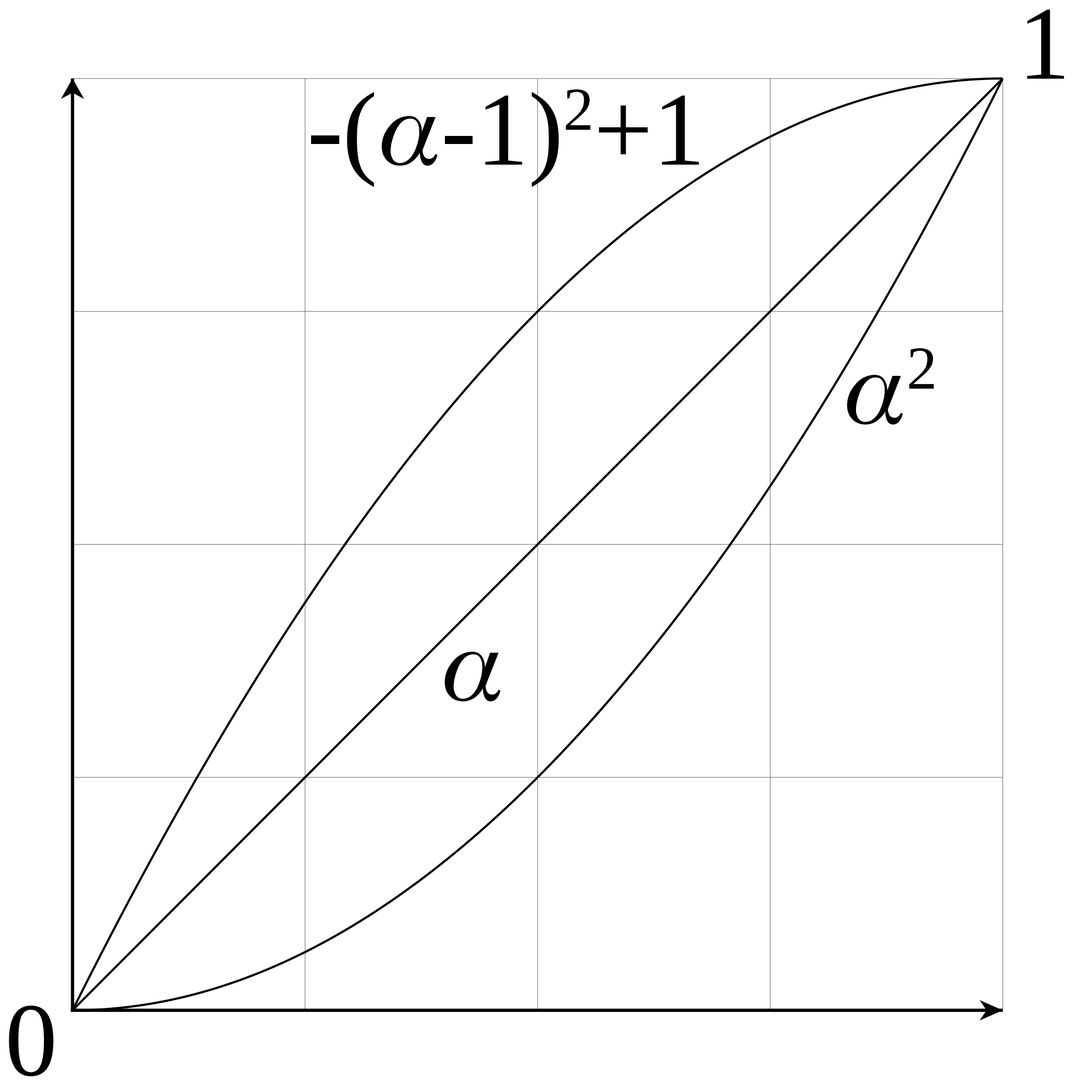
Our sparsity regularization term



		opacity optimization			
image	width × height	runtime (seconds)	RMSE	median error	max error
apple	500 × 453	330.3	1.8	0.0	32.3
bird	640 × 360	500.4	3.7	2.2	60.1
rowboat	589 × 393	981.4	3.3	2.4	19.2
buildings	589 × 393	317.9	2.3	1.4	32.2
cup	400 × 400	40.9	3.0	0.0	34.3
fruit	650 × 414	212.1	1.9	0.0	22.6
girls	589 × 393	152.7	2.4	1.4	29.1
hoover	500 × 500	47.1	3.9	1.0	39.2
light	504 × 538	101.6	2.4	1.0	25.5
robot	450 × 600	519.8	3.5	2.8	14.5
scrooge	410 × 542	97.6	2.6	1.4	15.7
Figure 4	500 × 500	434.3	0.7	0.0	3.3
trees	606 × 404	80.2	5.9	4.2	35.0
turtle	525 × 250	19.5	2.8	1.0	45.4
boat	480 × 600	520.0	4.2	2.2	40.2
castle	747 × 344	280.0	3.7	2.2	45.6
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Increase solver's tolerance values

Runtime	RMSE
39	1.9
68	3.8
140	4.2
54	2.3
21	2.8
38	2.0
49	2.7
29	3.9
46	2.3
50	3.7
38	2.6
37	1.5
53	5.8
15	2.8
105	2.2
66	3.6
129	2.7
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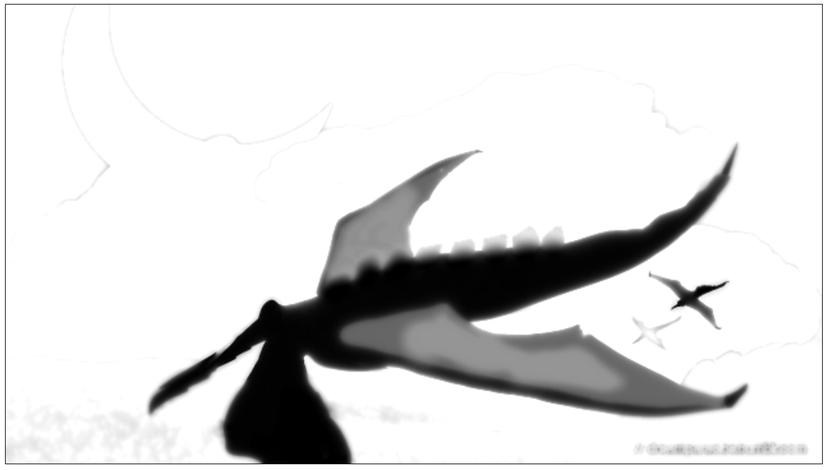
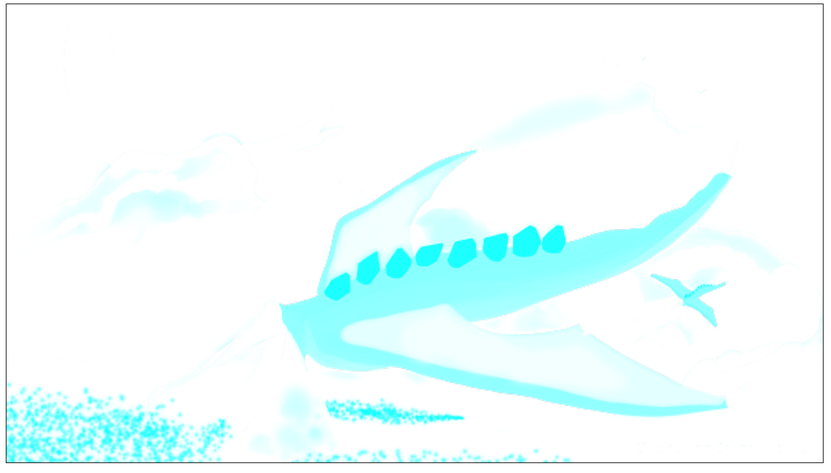
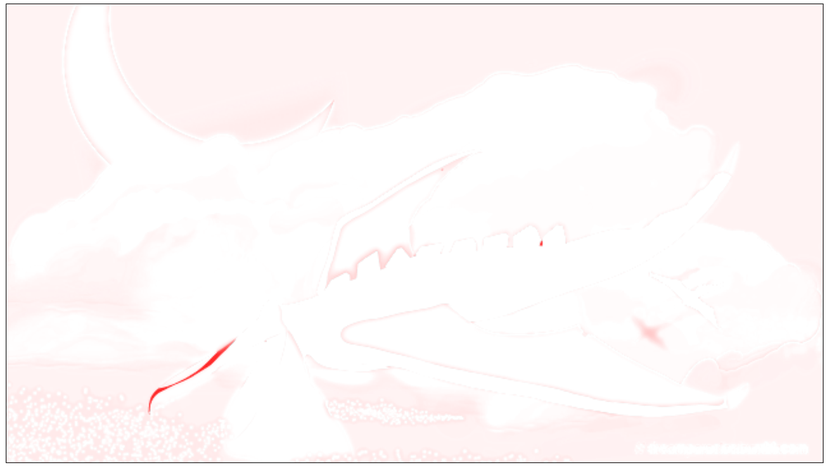
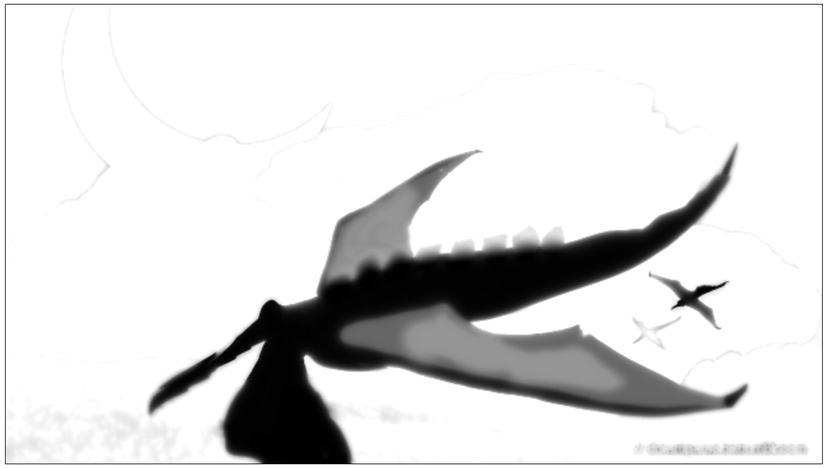
Much faster!

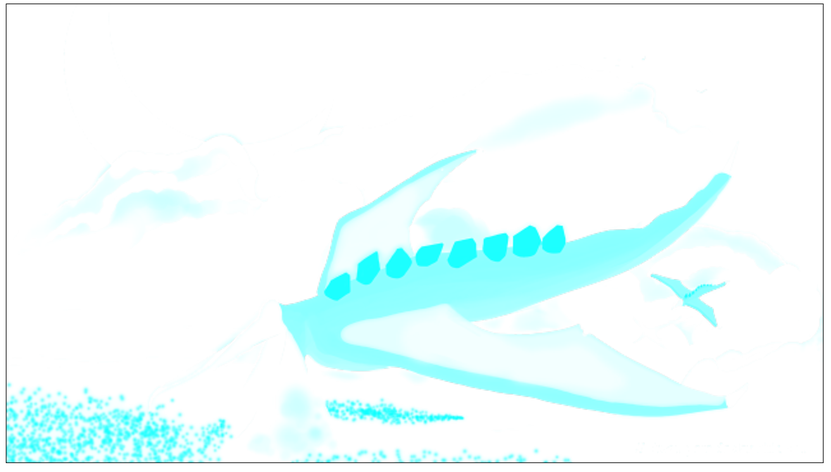
Results

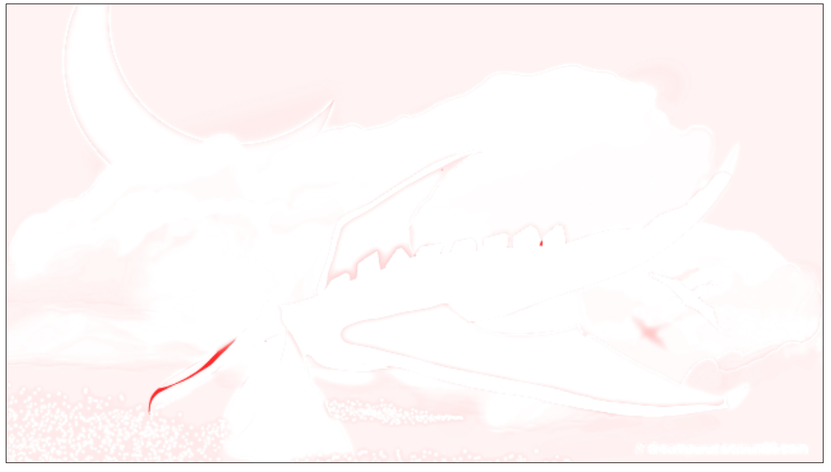

// dreamparacite.tumblr.com

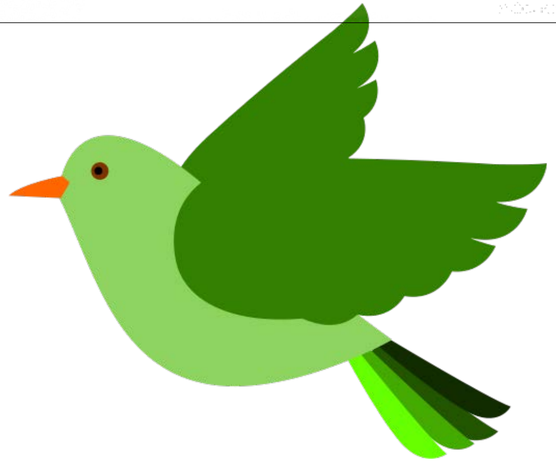






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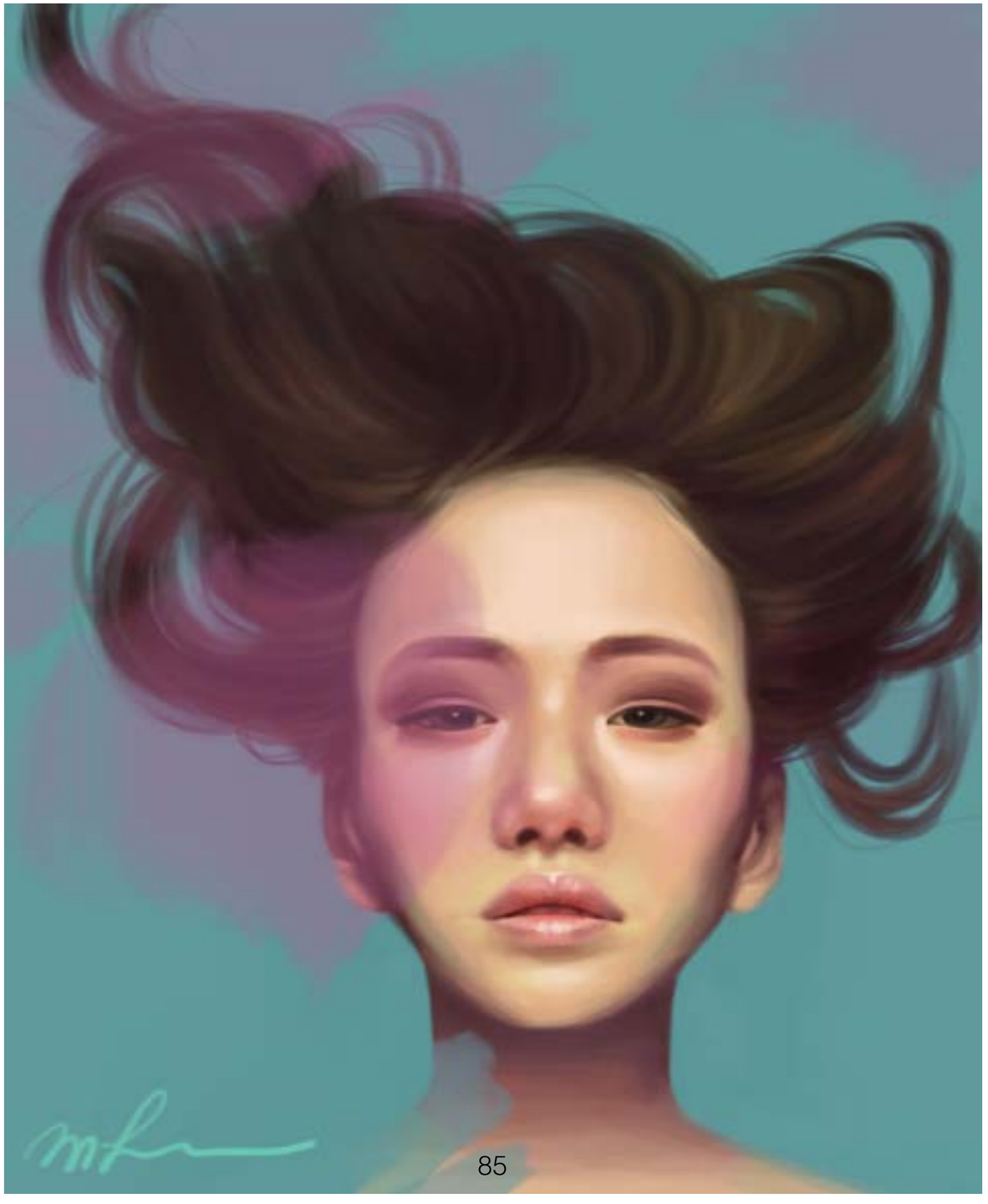

http://cargocollective.com/michellelee/

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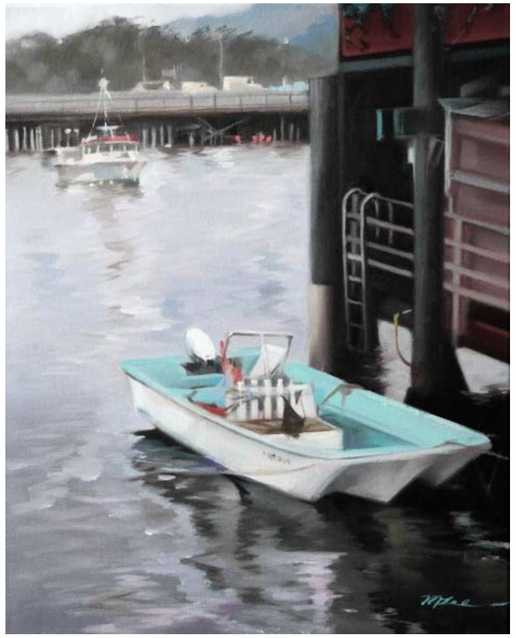
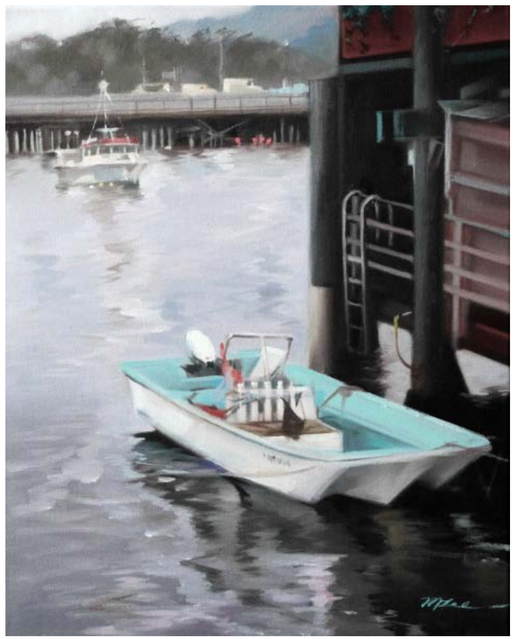
Local Recoloring

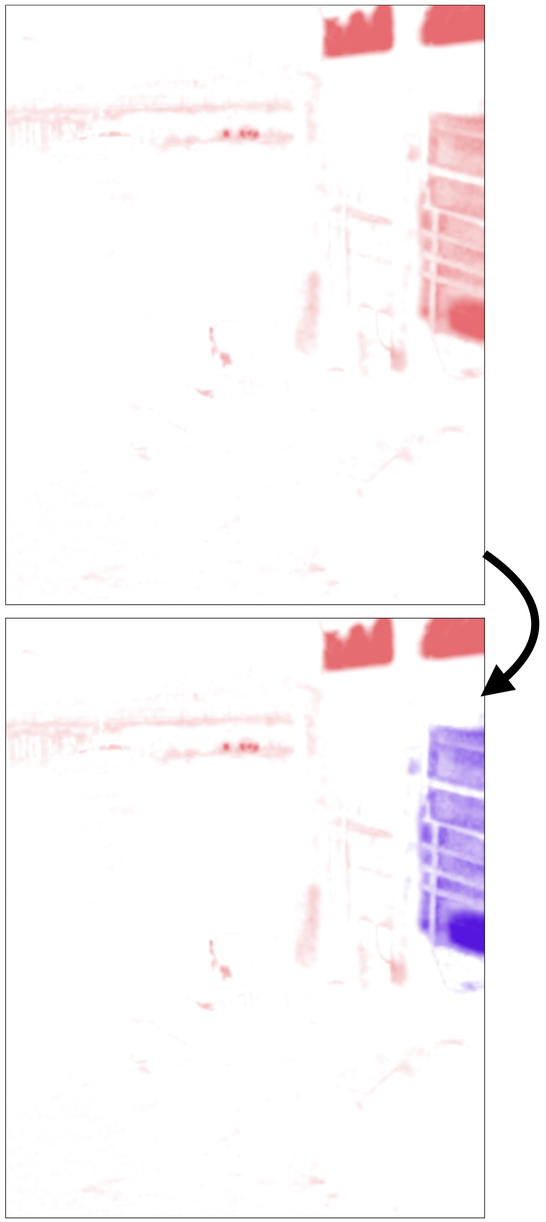
Original



Local Recoloring

Original





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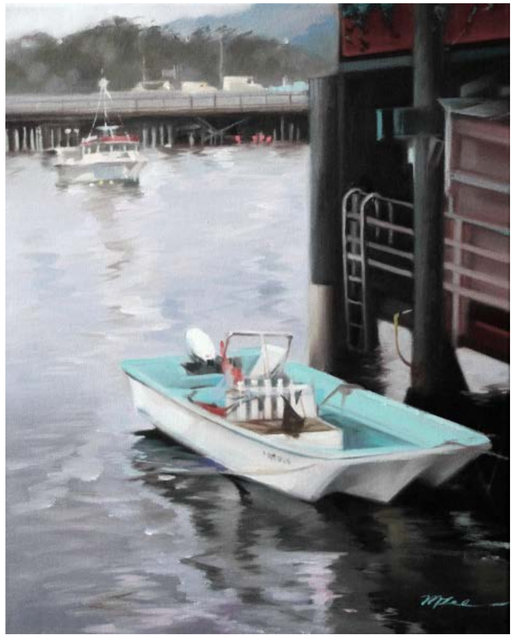

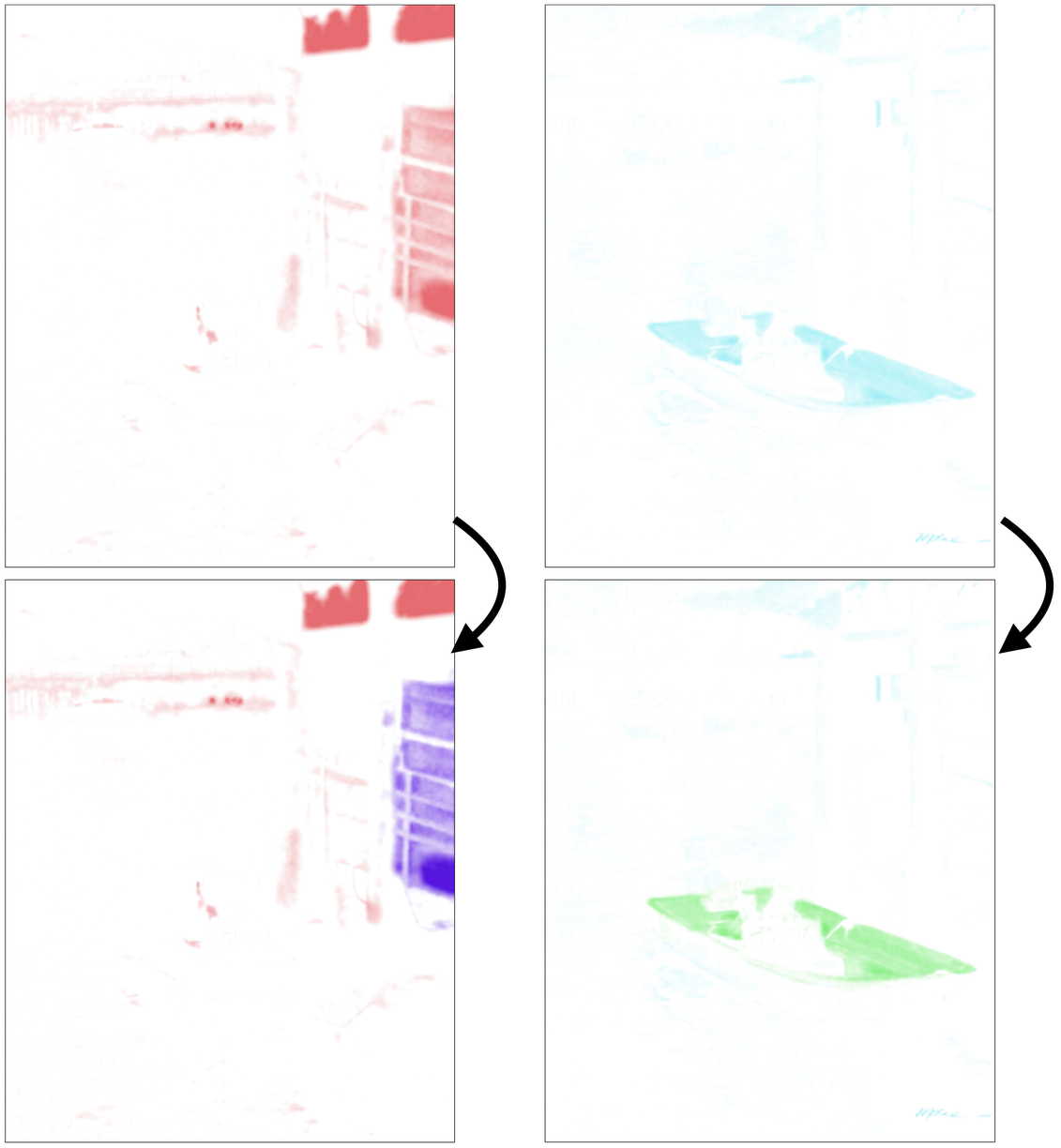

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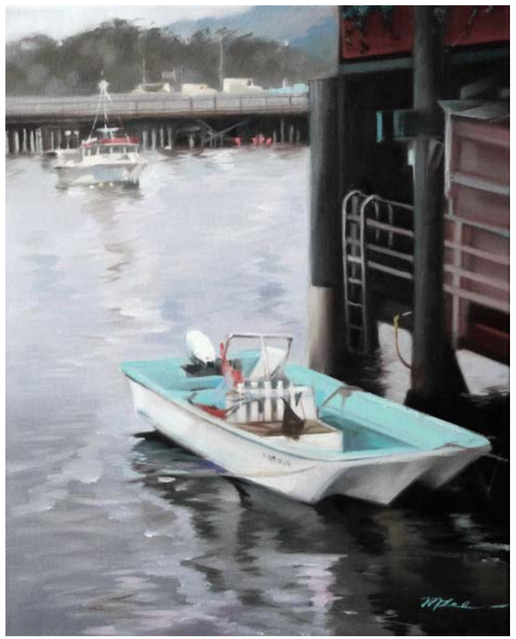
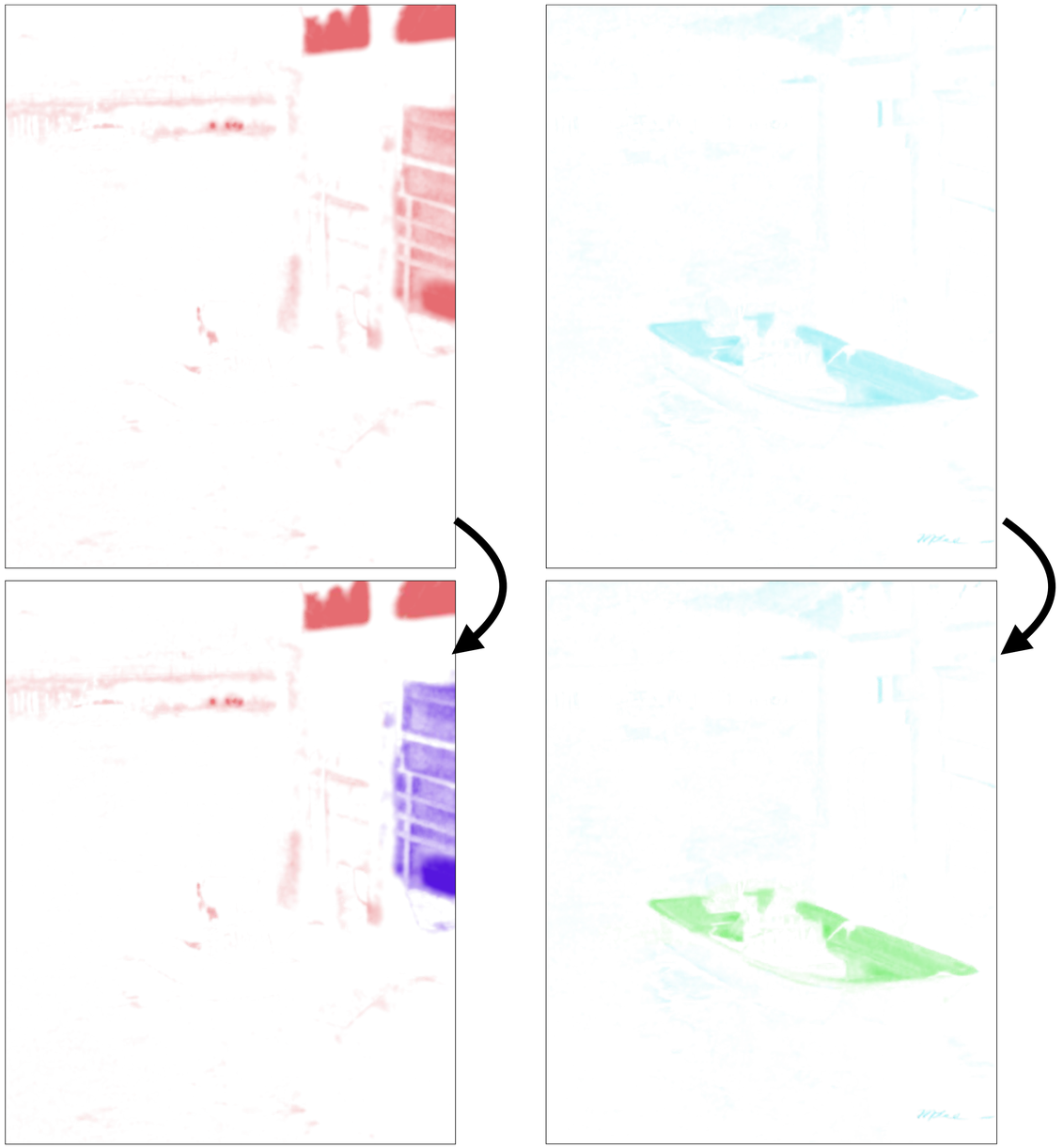
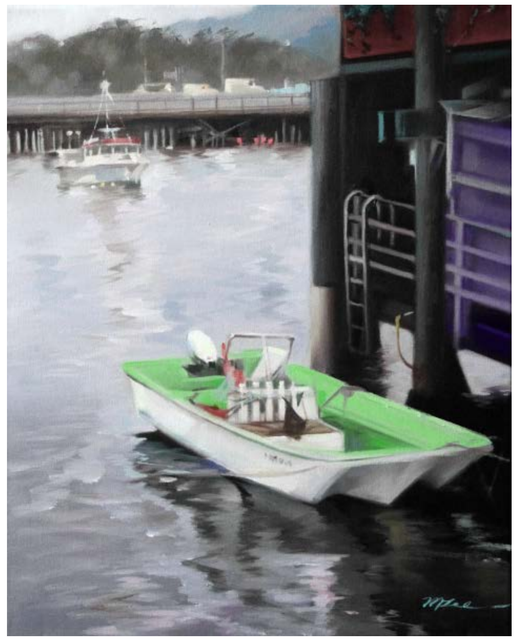
Original





Modified



Local Recoloring

Original

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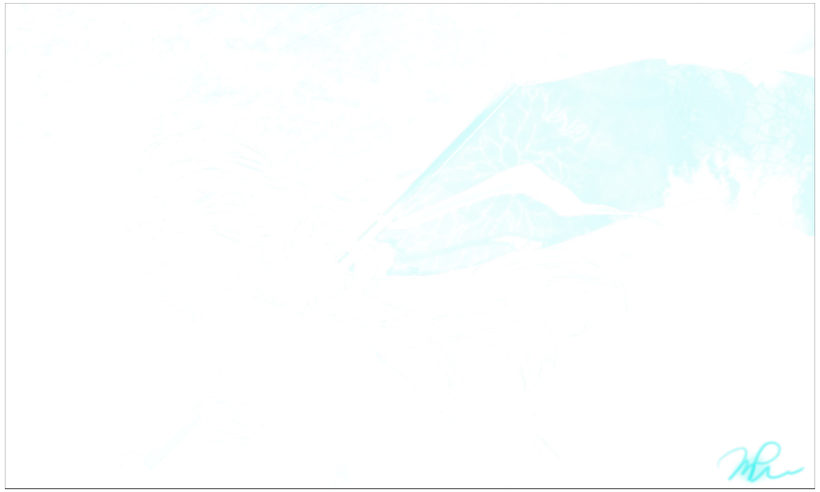
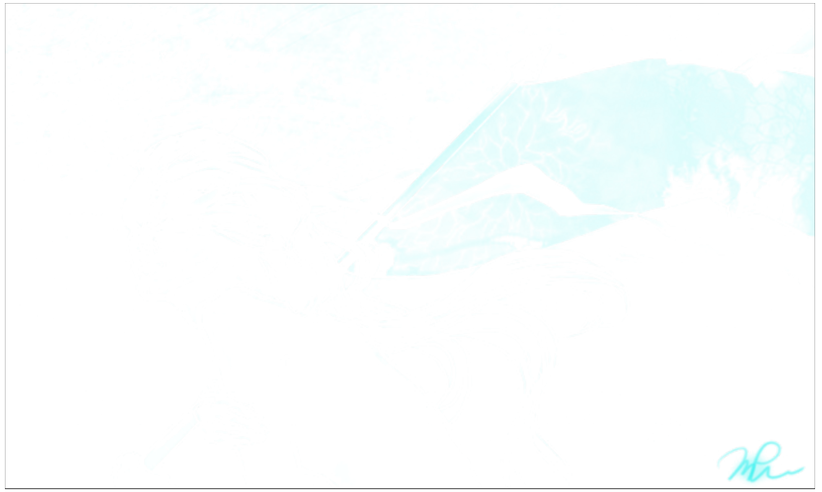


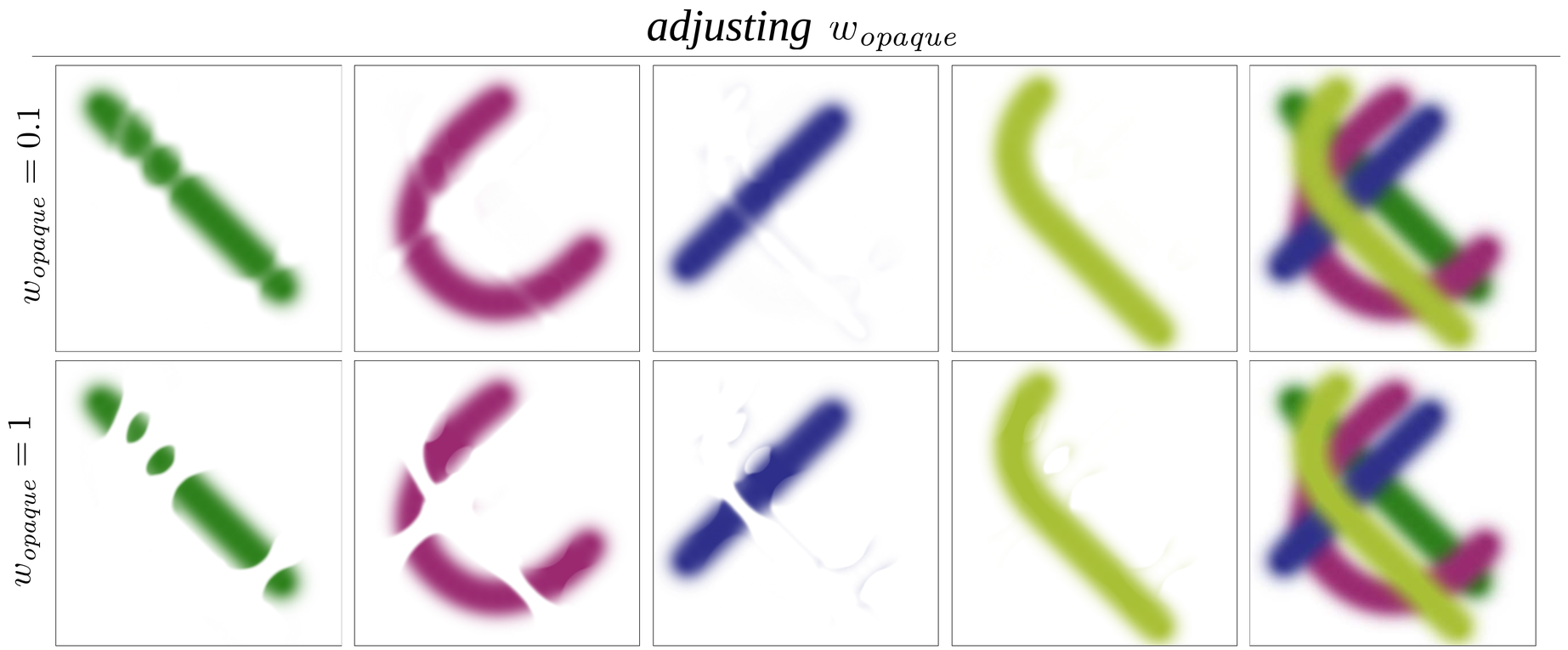
Local Recoloring

Original



Modified

Optimization parameters influence



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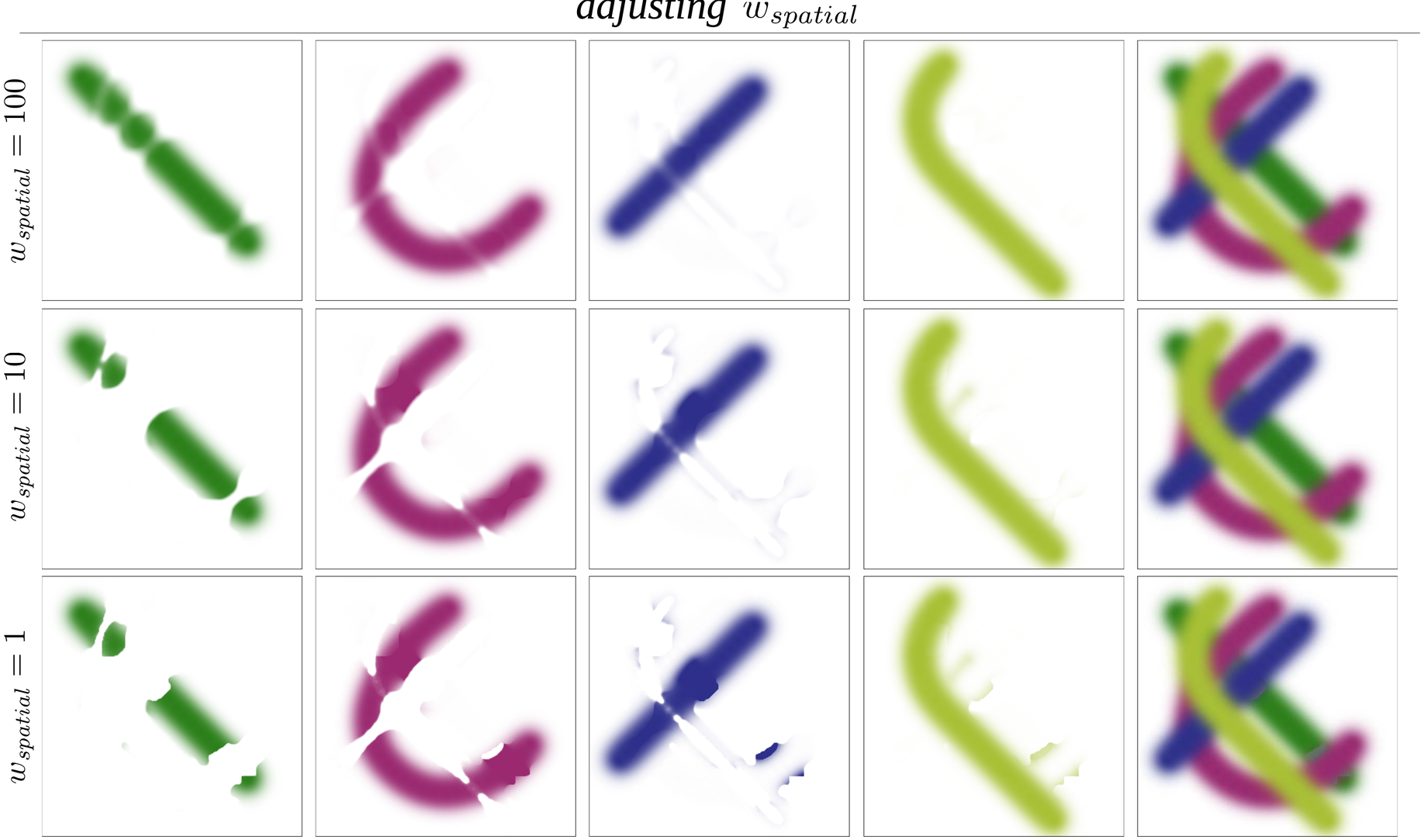
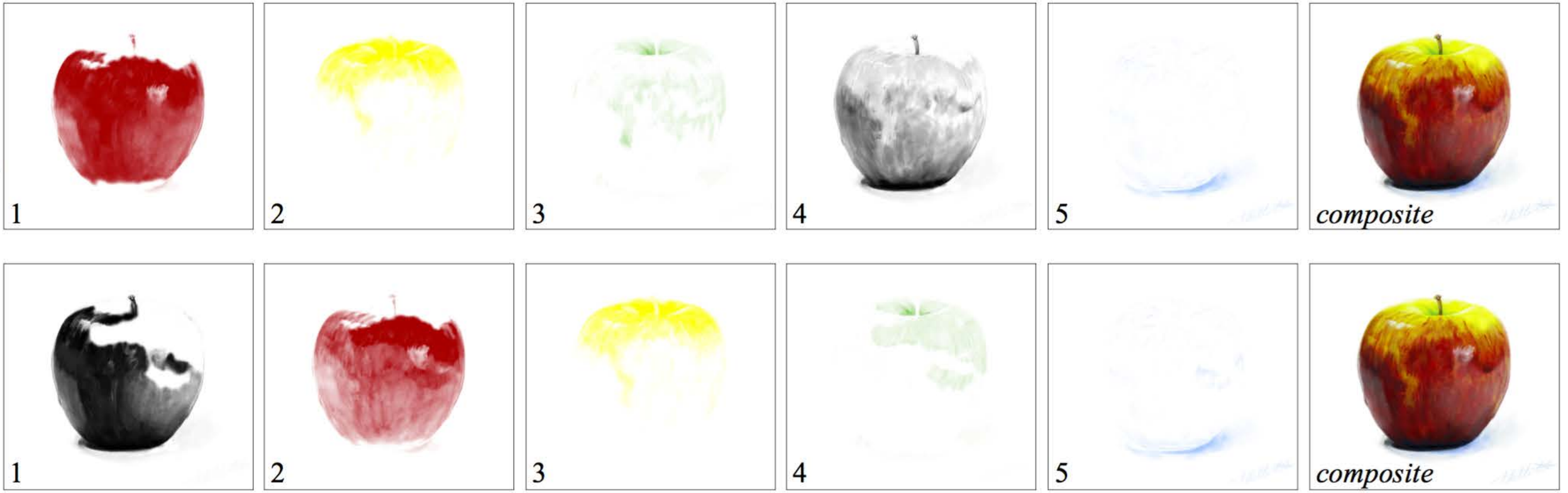


Layer order influence



Generalized Barycentric Coordinates

$$p = \sum w_i c_i$$

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$$p = c_n + \sum_{i=1}^{n} \left[(c_{i-1} - c_i) \prod_{j=i}^{n} (1 - \alpha_j) \right]$$

Alpha Compositing

Generalized Barycentric Coordinates

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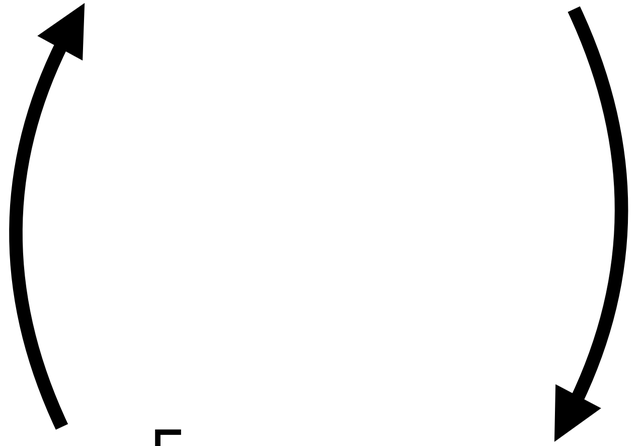

Ambiguous

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layer opacities

Alpha Compositing

GBC and Opacity conversions

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Opacity to GBC (Unique)

$$w_i = \begin{cases} \prod_{j=i+1}^{n}(1-\alpha_j) & \text{if } i = 0 \\ \left(\prod_{j=i+1}^{n}(1-\alpha_j)\right) - \left(\prod_{j=i}^{n}(1-\alpha_j)\right) & \text{if } 0 < i < n \\ 1 - \prod_{j=i}^{n}(1-\alpha_j) = \alpha_i & \text{if } i = n \end{cases}$$

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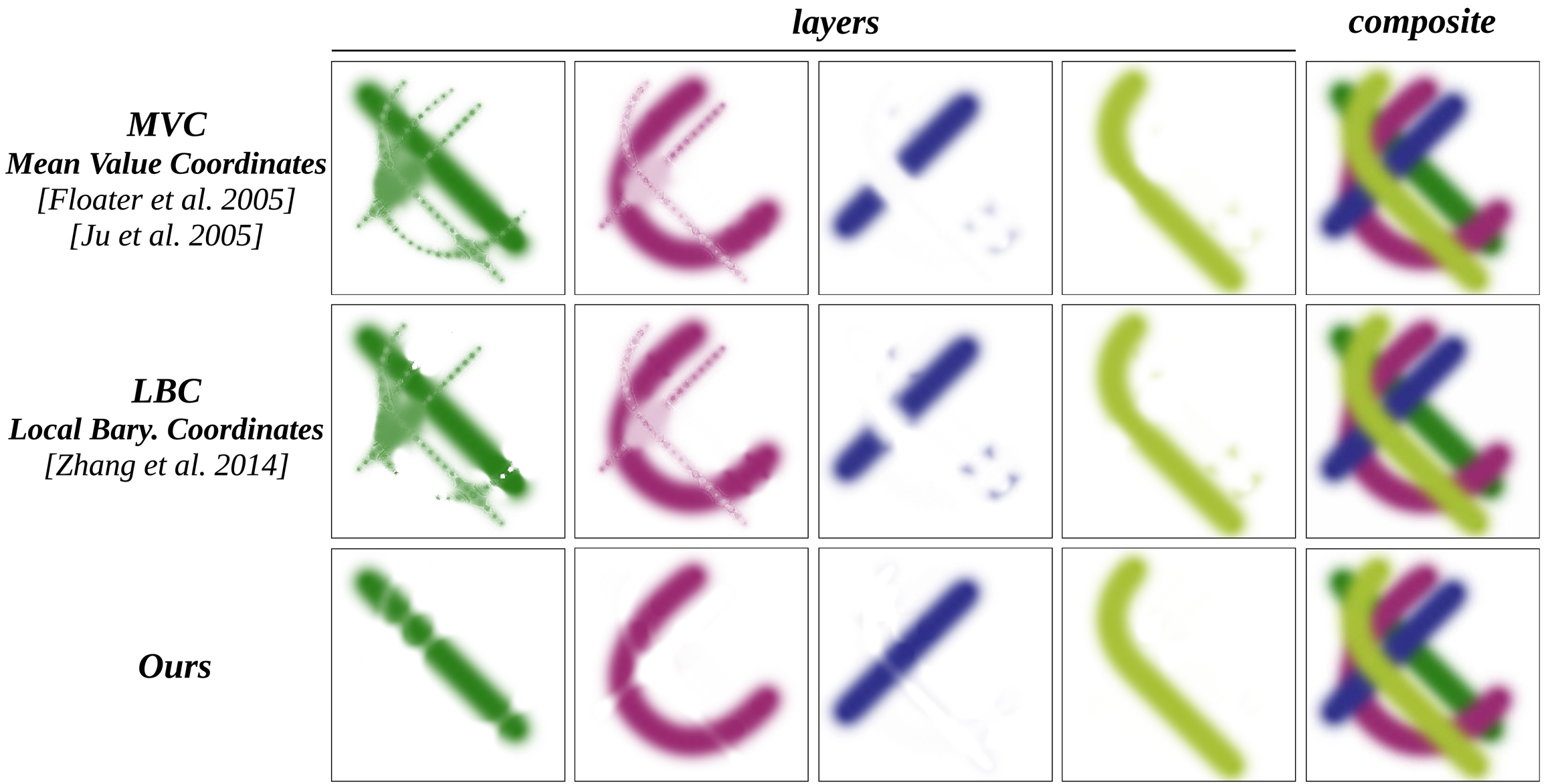
Generalized Barycentric Coordinates



Demo

Our layer opacities can also be uniquely converted into Generalized Barycentric Coordinates.

Actually, we now get additive mixing layers, which is layer order independent.

Global Recoloring

Visualize the colors of an image as a 3D RGB point cloud.

apple.png

width: 500, height: 453

total pixels: 226500

unique pixels: 226500

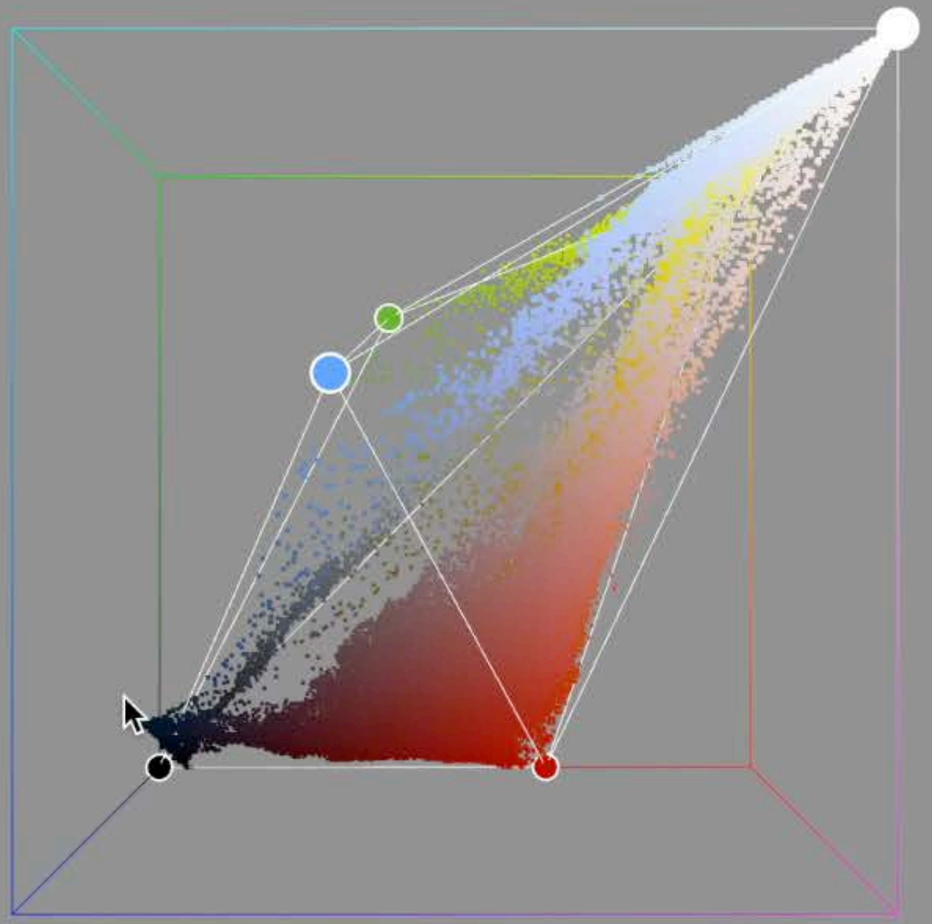
Choose File No file chosen

Rotation has intertia:

Look from white

Save Everything

Save Camera Only



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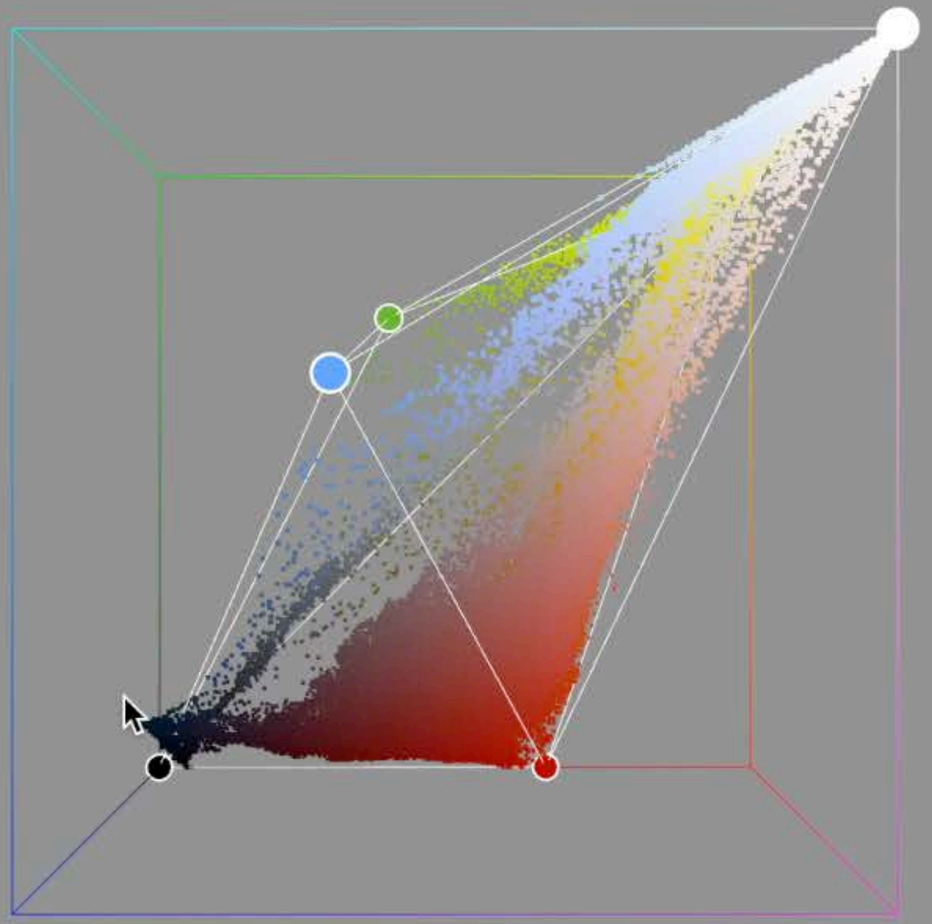
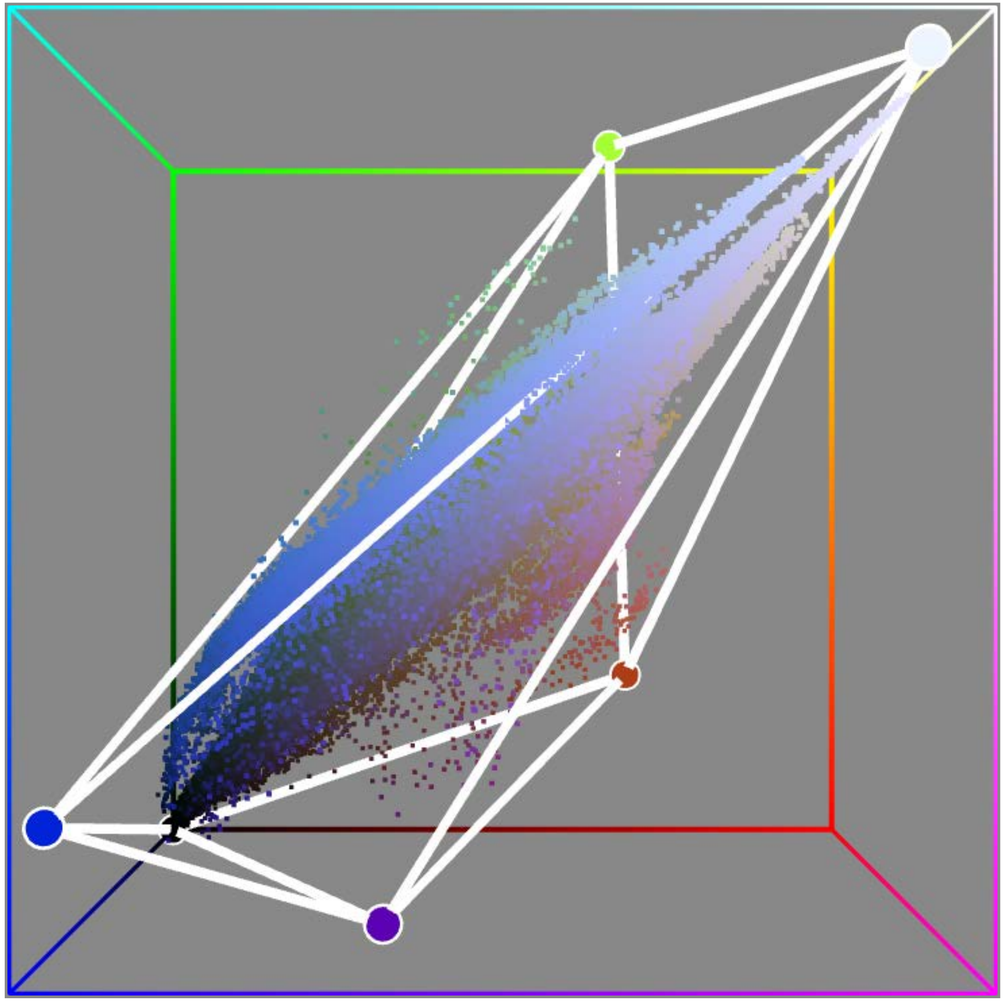


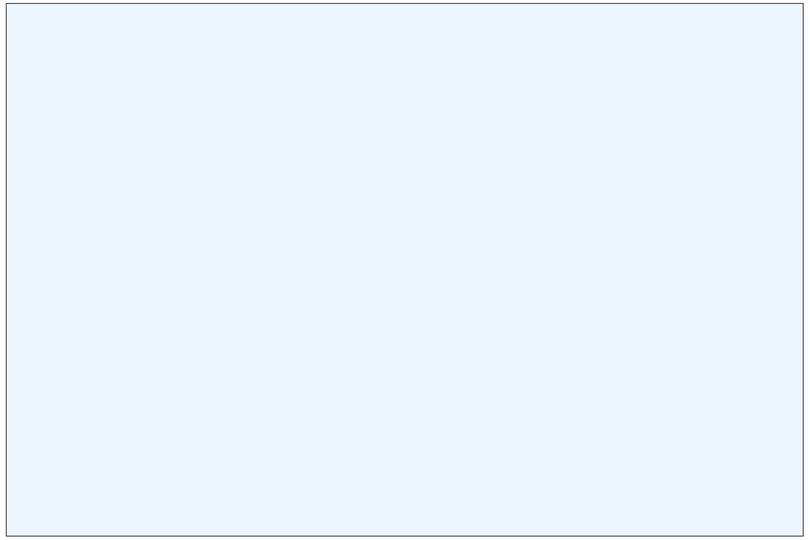
Natural Images

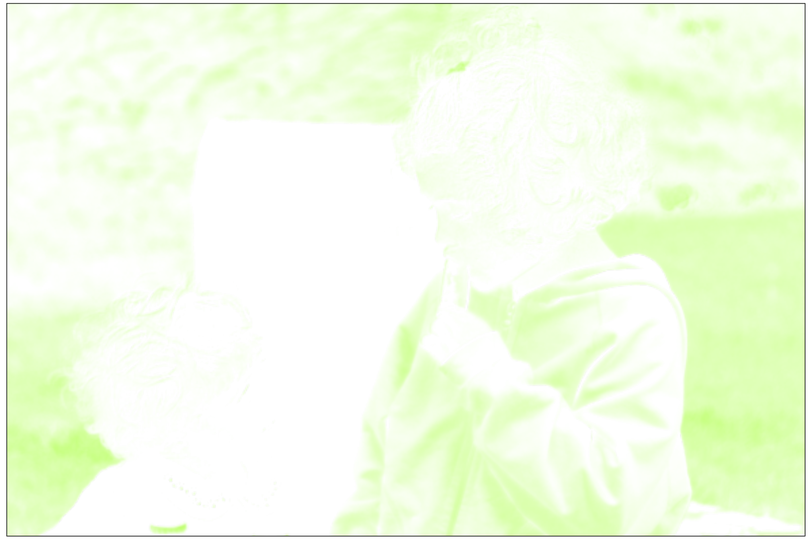
Original

Simplified hull



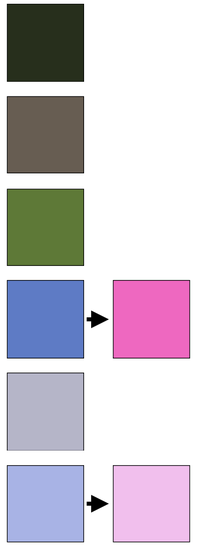
layers



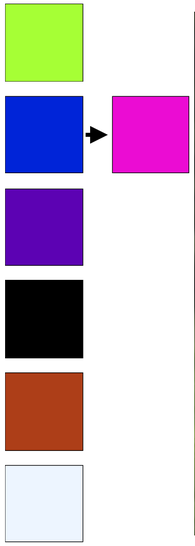


Global Recoloring Comparison

Original



Chang et al. 2015



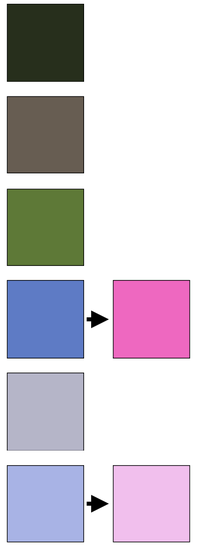
Ours

MVC

LBC

Global Recoloring Comparison

Original



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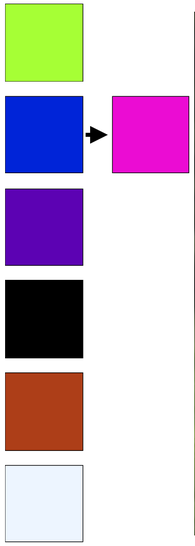

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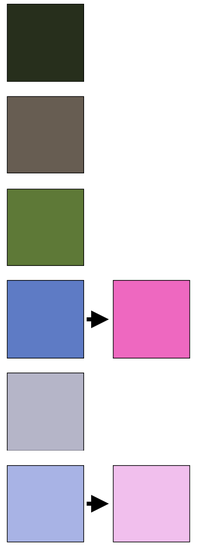
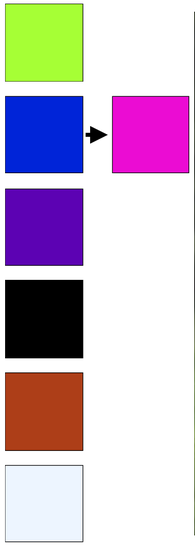


Chang et al. 2015



Ours

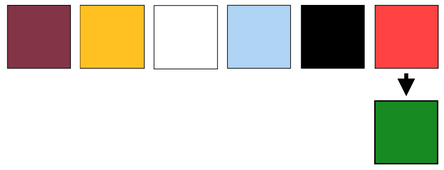
MVC

LBC

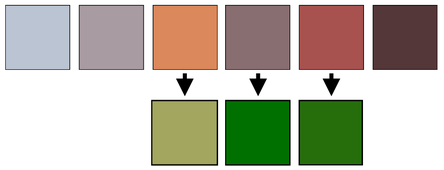
Global Recoloring Comparison

Original

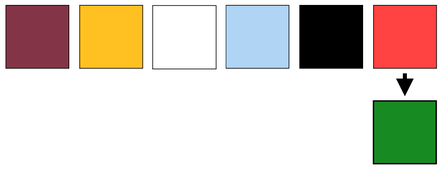
Ours



Chang et al. 2015



MVC



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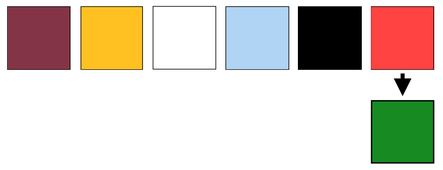

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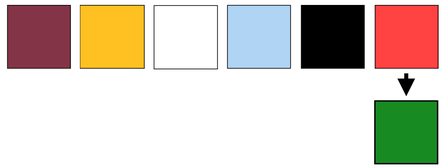
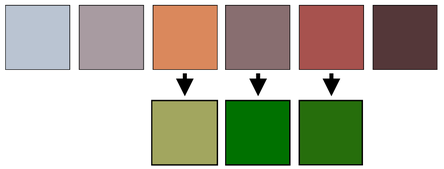
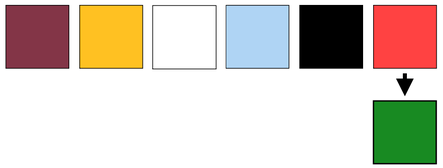


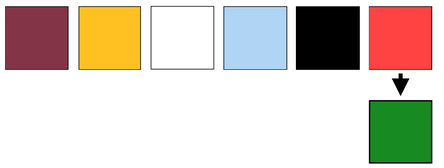
Chang et al. 2015



MVC



LBC



Global Recoloring Comparison

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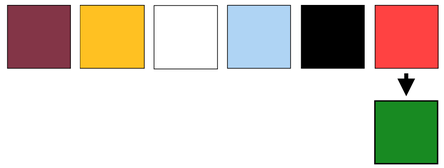

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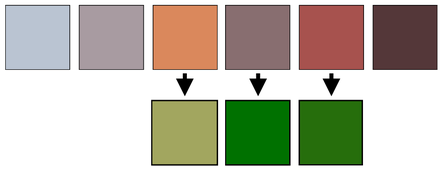

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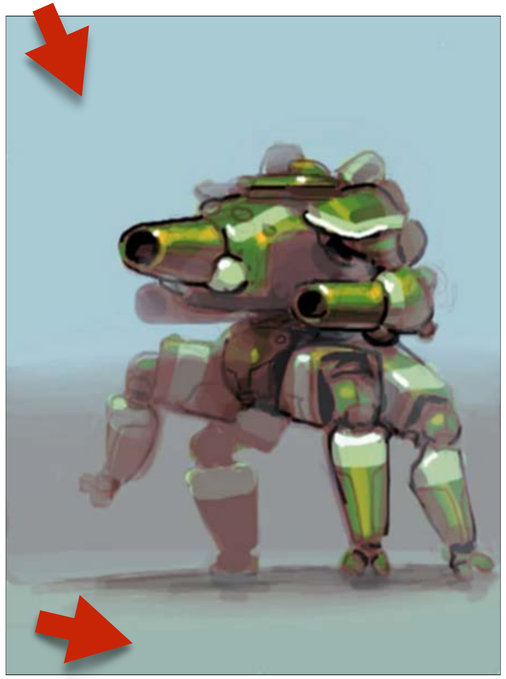

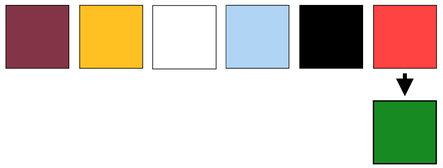

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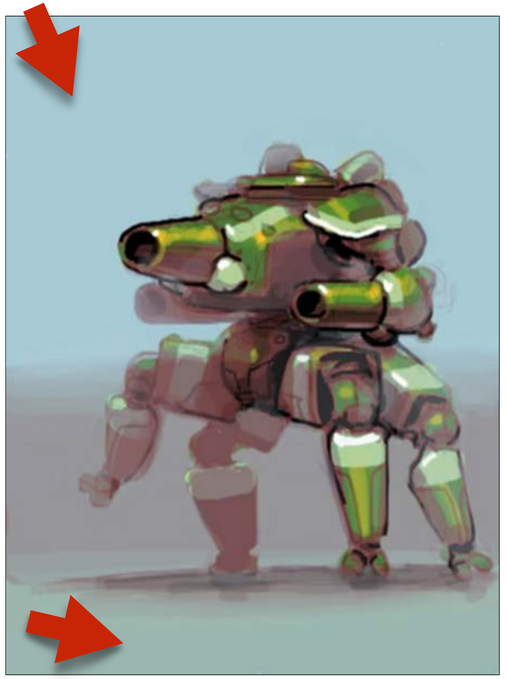
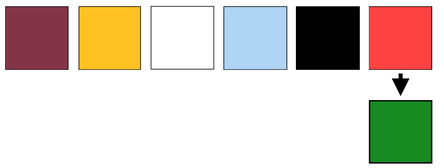




Weights Sparsity Comparison

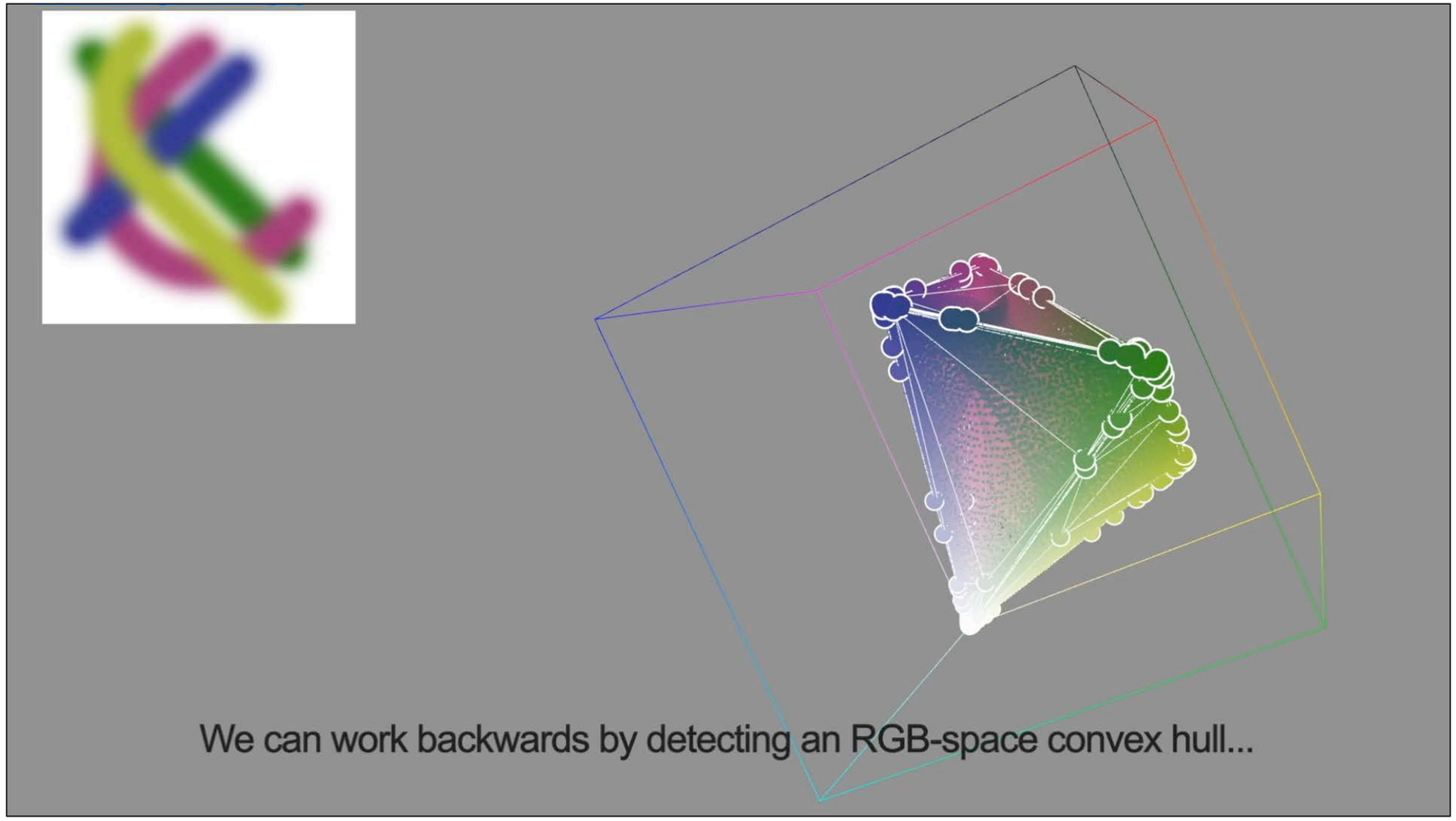
image	MVC	LBC	Our optimization
apple	0.54	0.59	0.62
rowboat	0.11	0.34	0.44
girls	0.10	0.22	0.36
robot	0.01	0.14	0.47
scrooge	0.30	0.38	0.51
Figure 4	0.33	0.38	0.41
boat	0.08	0.24	0.49

Sparsity is computed as the fraction of near-zero values in weights matrix.

$$\epsilon = \frac{1/512}{\#\text{vertices}}$$

Summary

- The RGB-space geometry of an image contains a hidden geometric structure.



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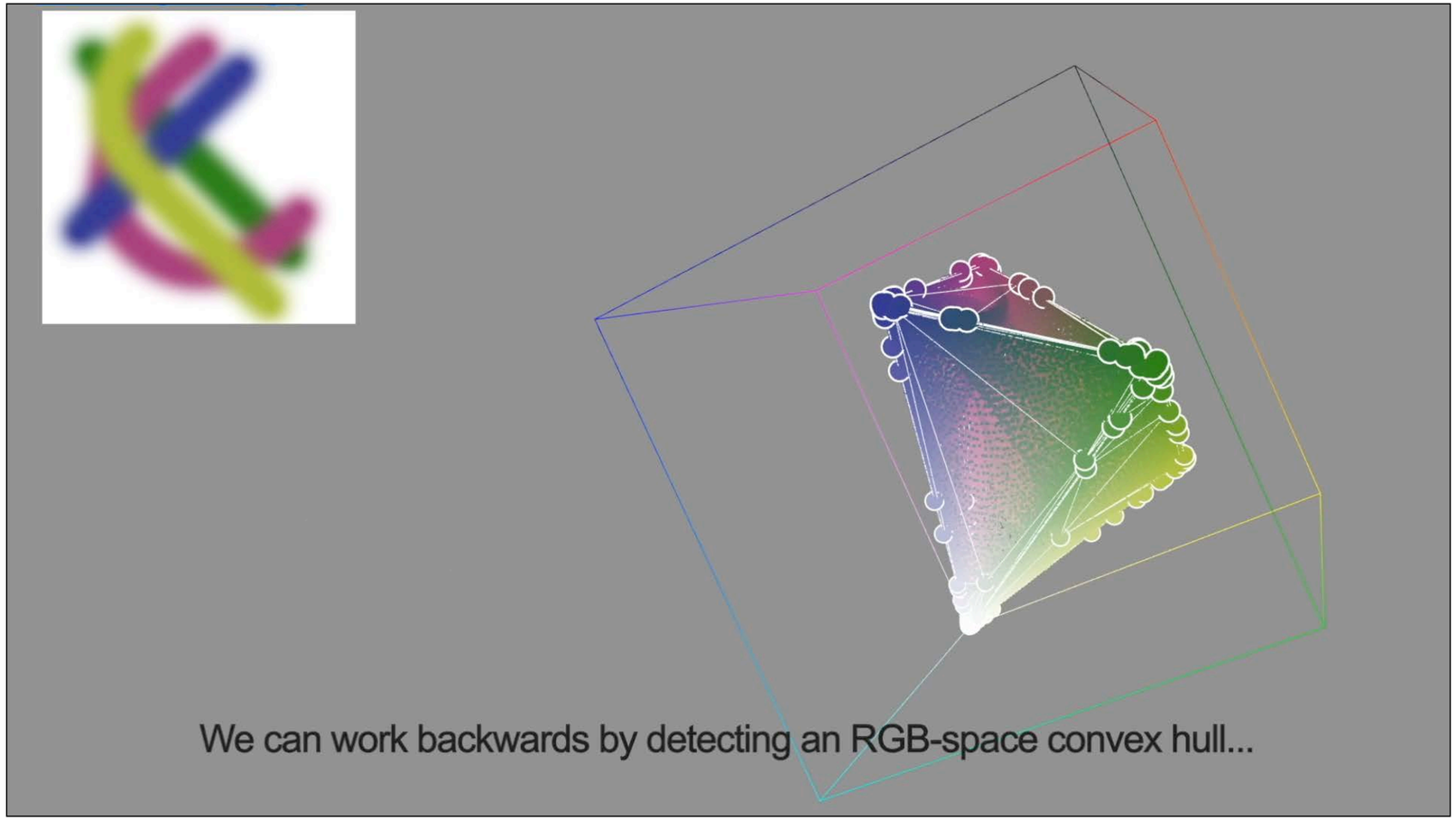

Summary

- We regularize the under-constrained layer opacity problem by balancing sparsity and smoothness.

Original

We then solve an optimization problem to extract translucent layers.

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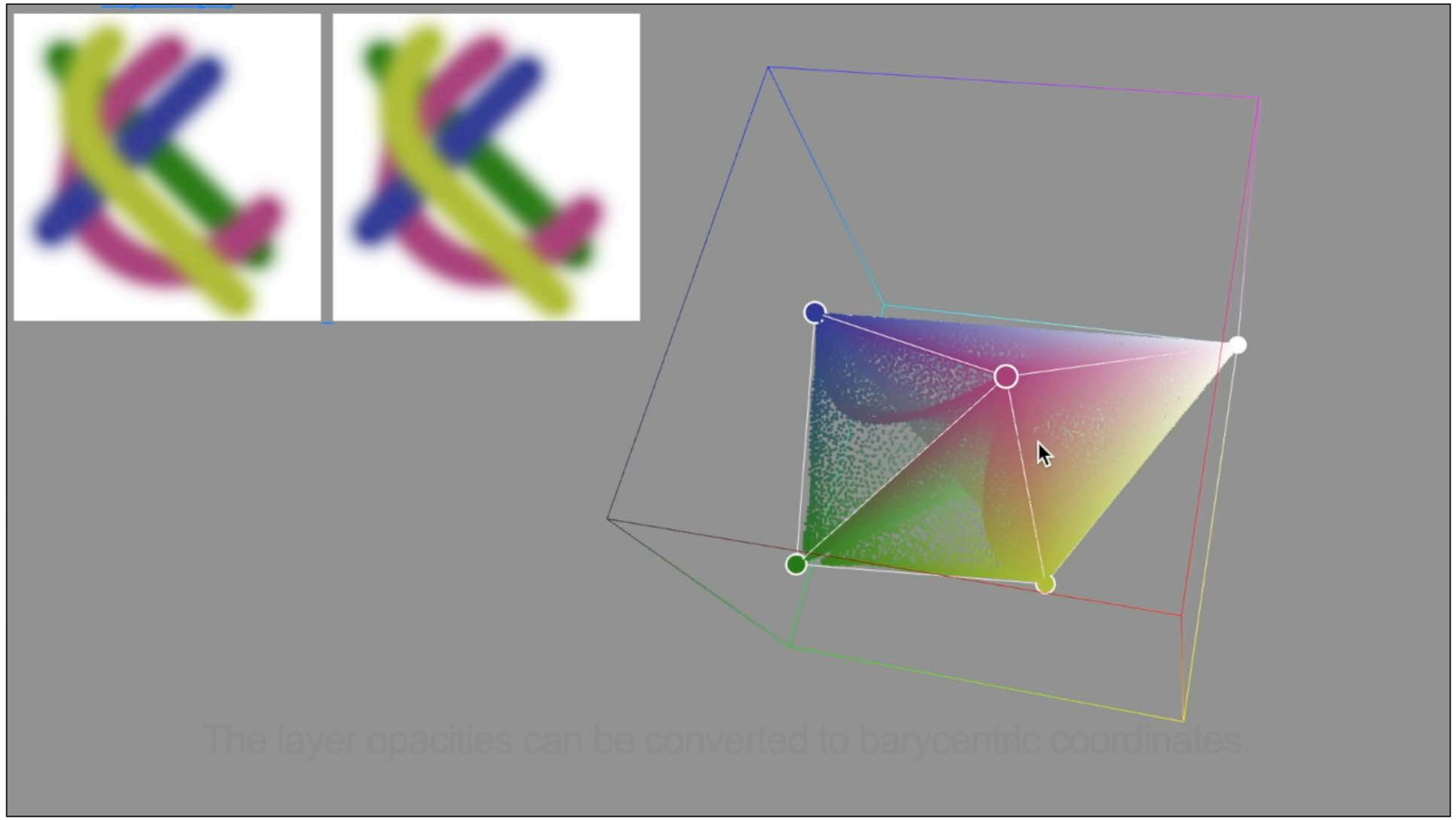

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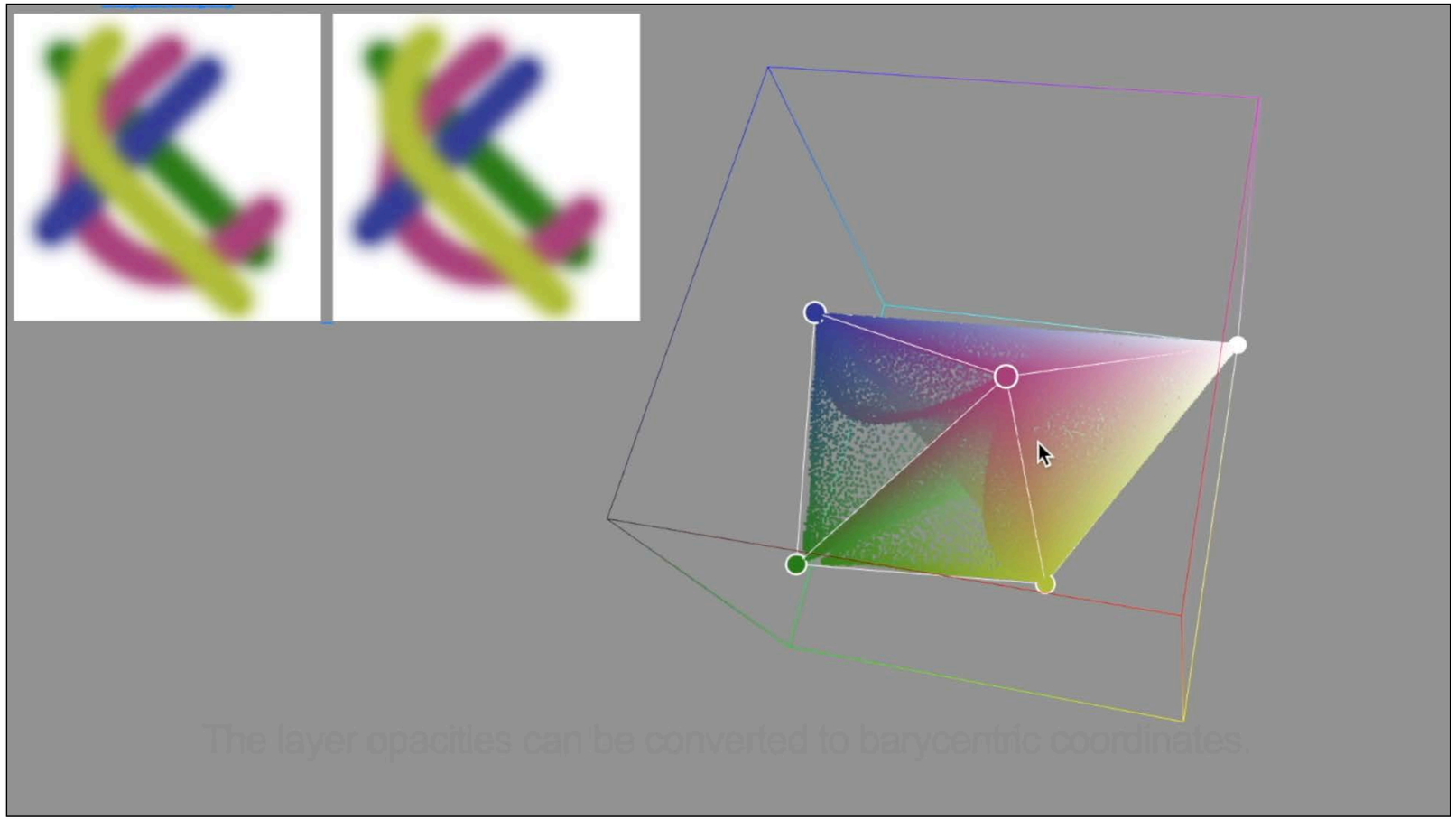
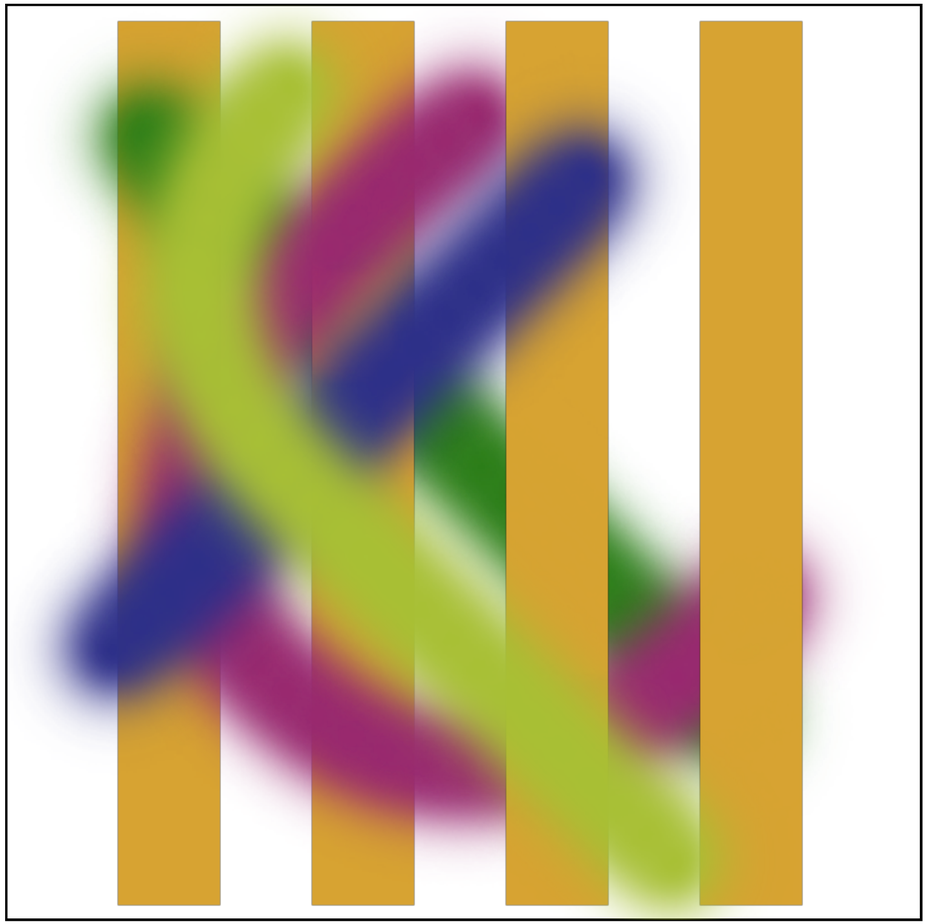


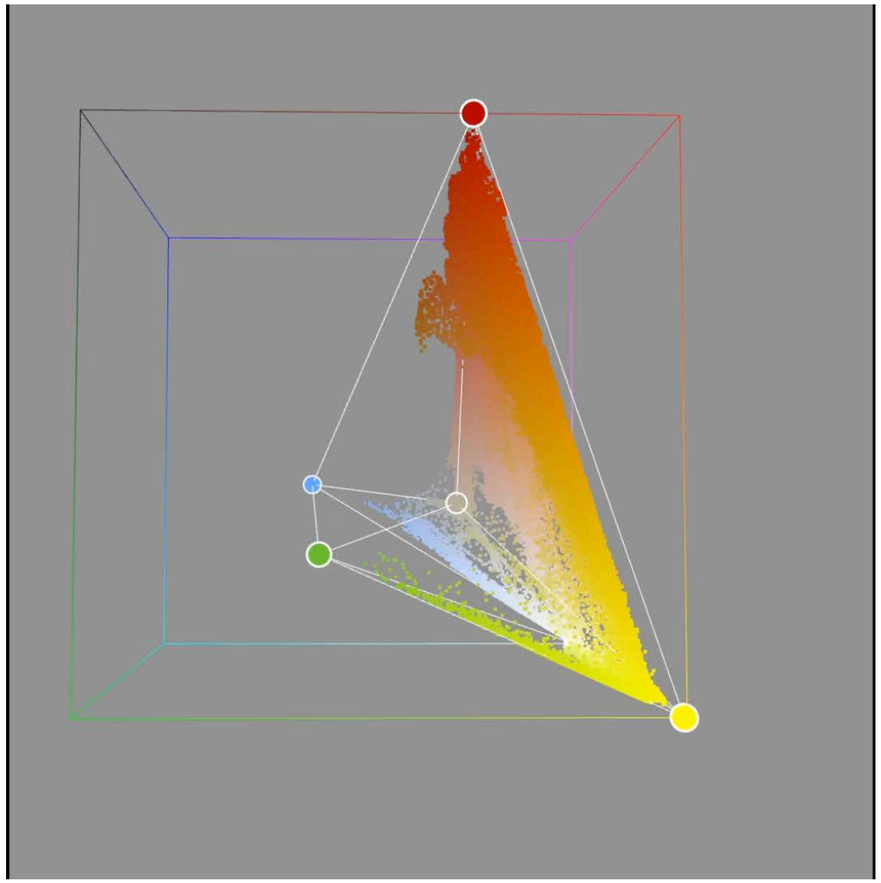
Limitation

- We use a global order for layers, which may not match true editing history.



Limitation

- Pigment colors that lie within the convex hull cannot be detected.



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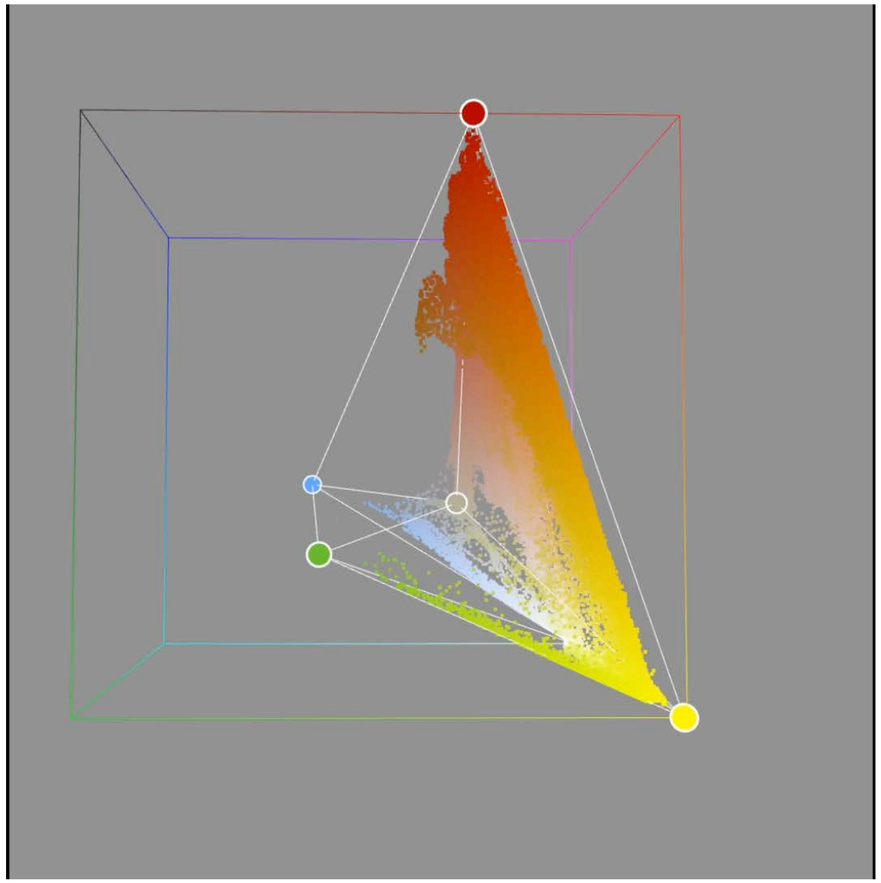

Limitation

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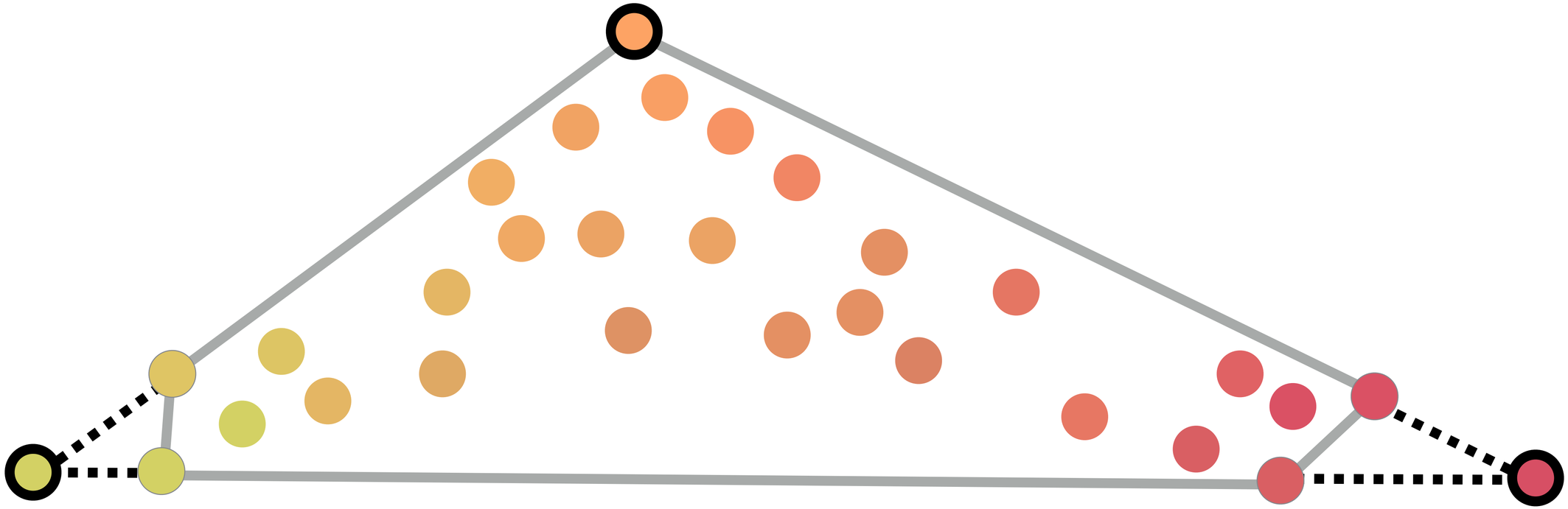

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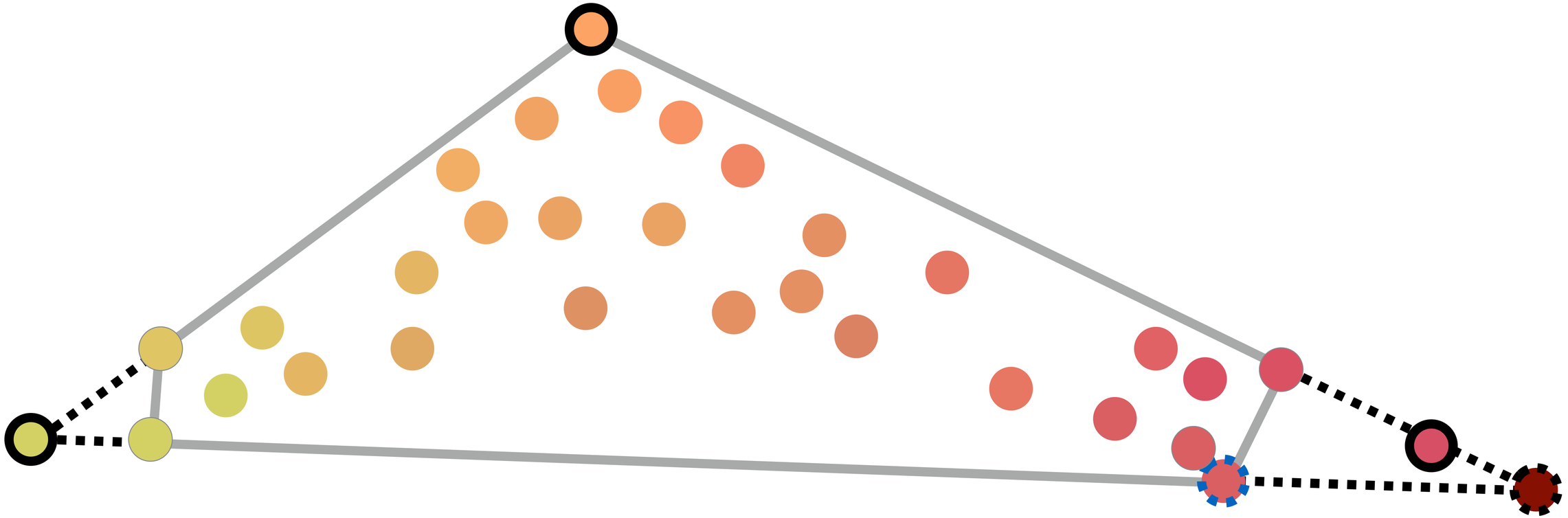

Future Work

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$$\mathbf{E} = \|\text{original} - \text{reconstructed image}\|^2 \quad \sum ||P_i - w_{ij}C_j||^2$$

$$+$$

$$\text{Per pixel mixing weights sparsity} \quad \sum -(1 - w_{ij})^2$$

$$+$$

$$\text{Mixing weights spatial smoothness} \quad (\textbf{Laplacian})$$

Thank You!

- Contact Information
  - Jianchao Tan: jtan8@gmu.edu
  - Jyh-Ming Lien jmlien@gmu.edu
  - Yotam Gingold: ygingold@gmu.edu
- Project Website (GUI, code, data): https://cragl.cs.gmu.edu/singleimage/
- Artists: Adelle Chudleigh; Dani Jones; Karl Northfell; Michelle Lee; Adam Saltsman; Yotam Gingold.
- Sponsors:
  - United States National Science Foundation, Google.

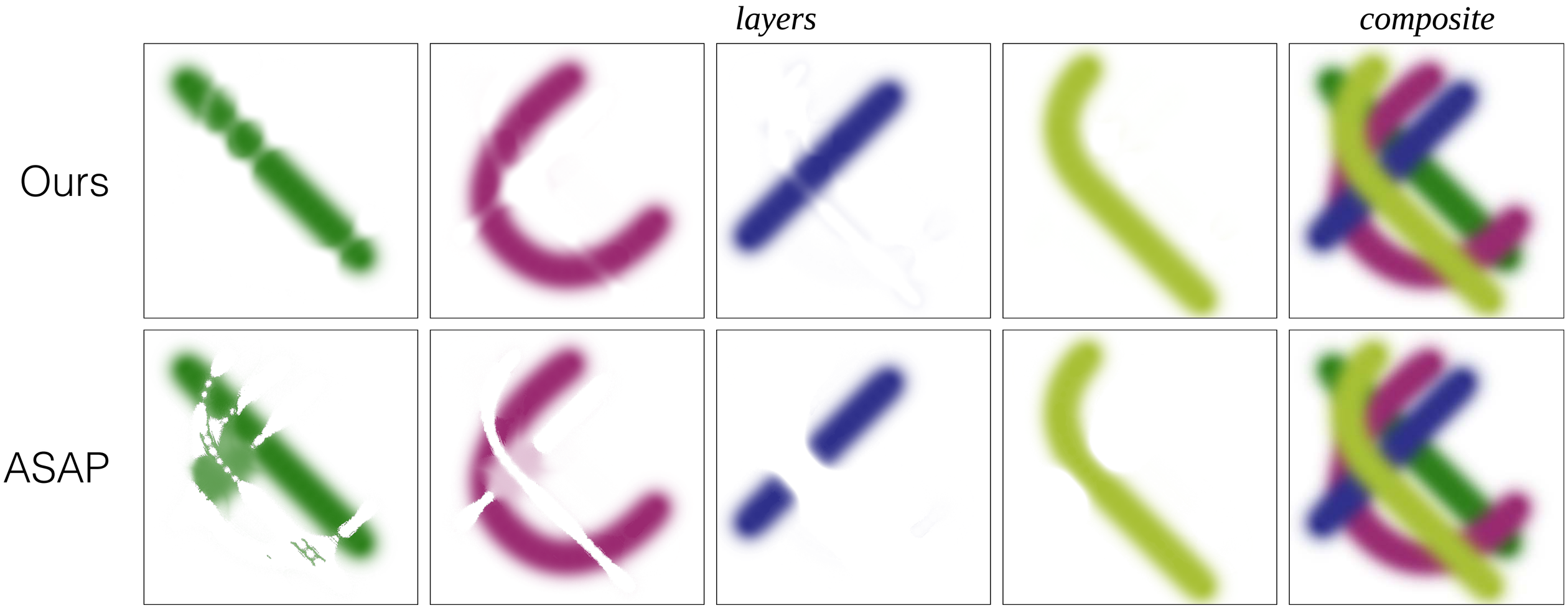
Extra Slides

As-sparse-as-possible(ASAP)

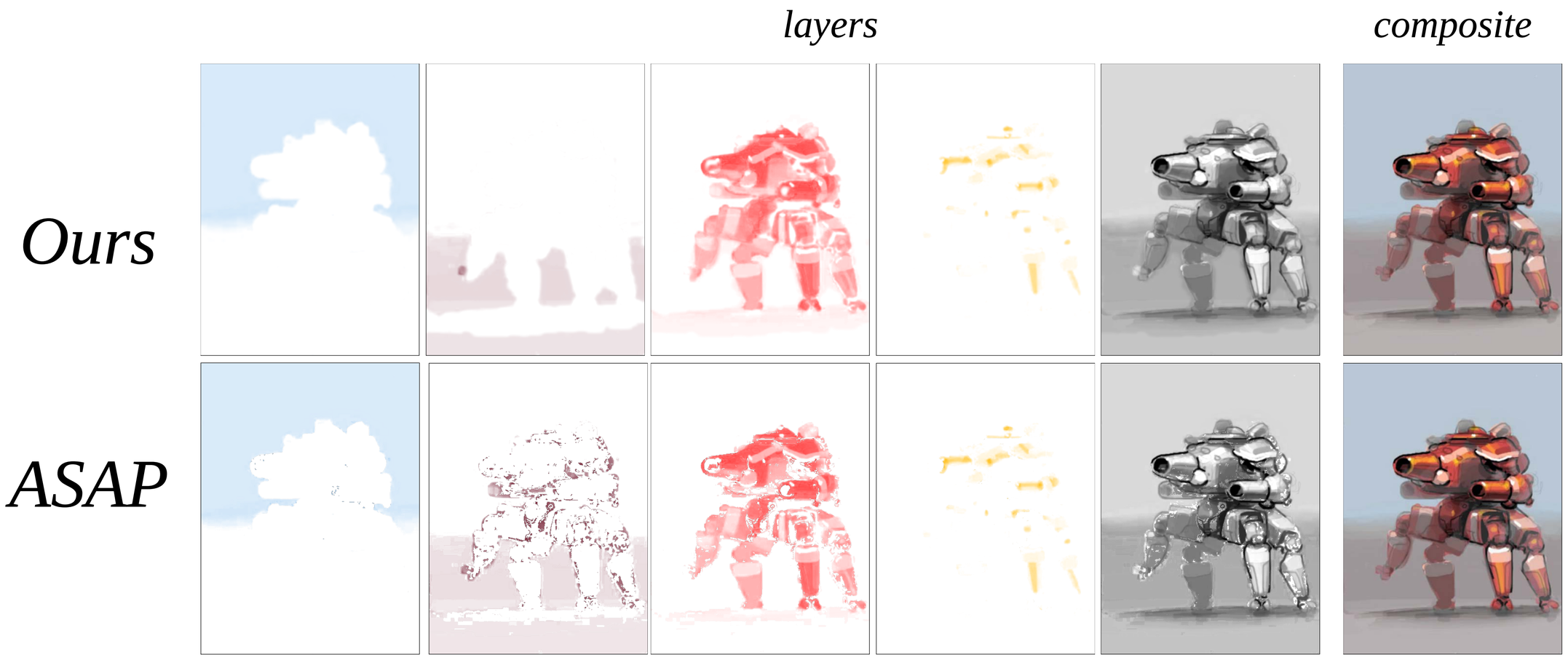
The sparsest possible weights have at most four non-zero weight values. In other words, a pixel can always be expressed as the weighted average of four colors. This corresponds to the well-defined, non-generalized barycentric coordinates of any tetrahedron enclosing color p whose vertices are a subset of the palette colors.

If the user has identified an background color as the bottom-most layer, the ASAP weights will assume that all pixels are the mixture of at most three non-background colors.

As-sparse-as-possible(ASAP)

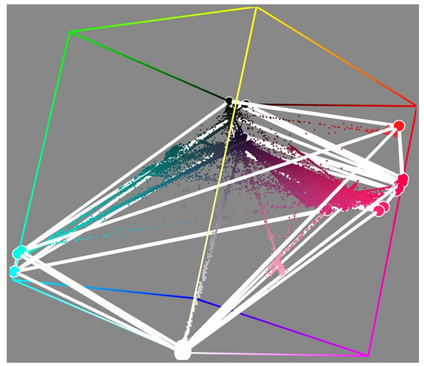


As-sparse-as-possible(ASAP)

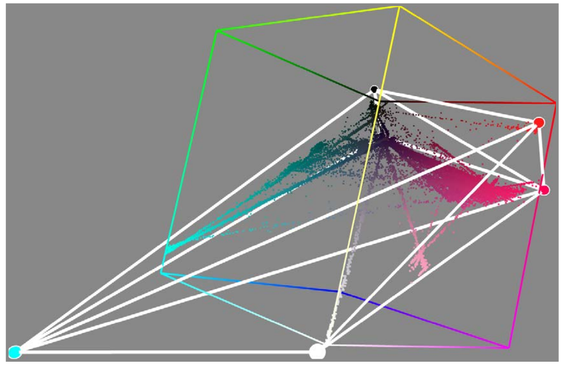


Post vertex brute force optimization led to an improvement in vertex positions.

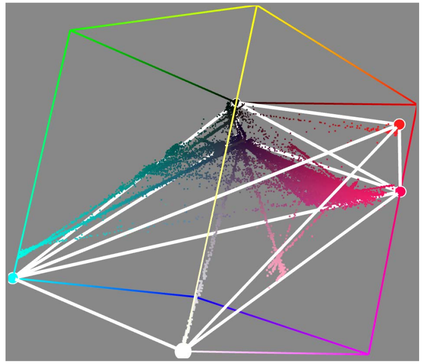
input image



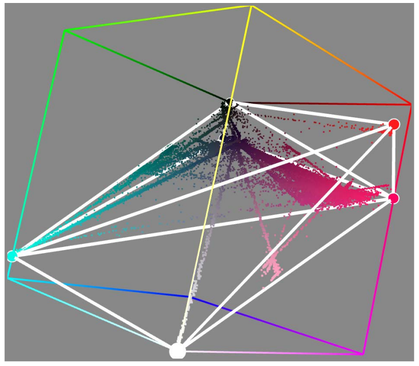
convex hull



simplified hull with invalid colors



projected hull



optimized hull

Spectral Matting [Levin et al. 2008]

input

9 components

1

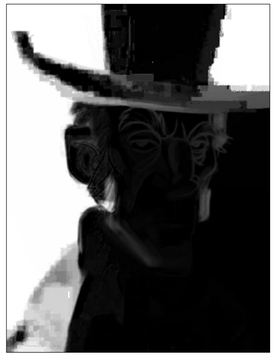
2

3

4

5

6



7

8

9

k-means

best alpha matte