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Semi-supervised Parametric Real-world Image Harmonization

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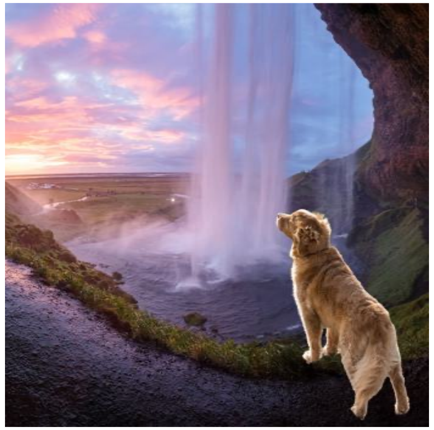
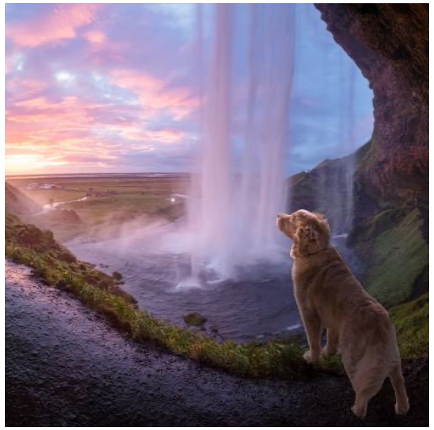
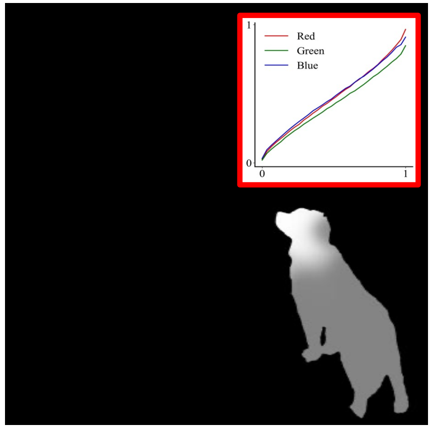
Project page

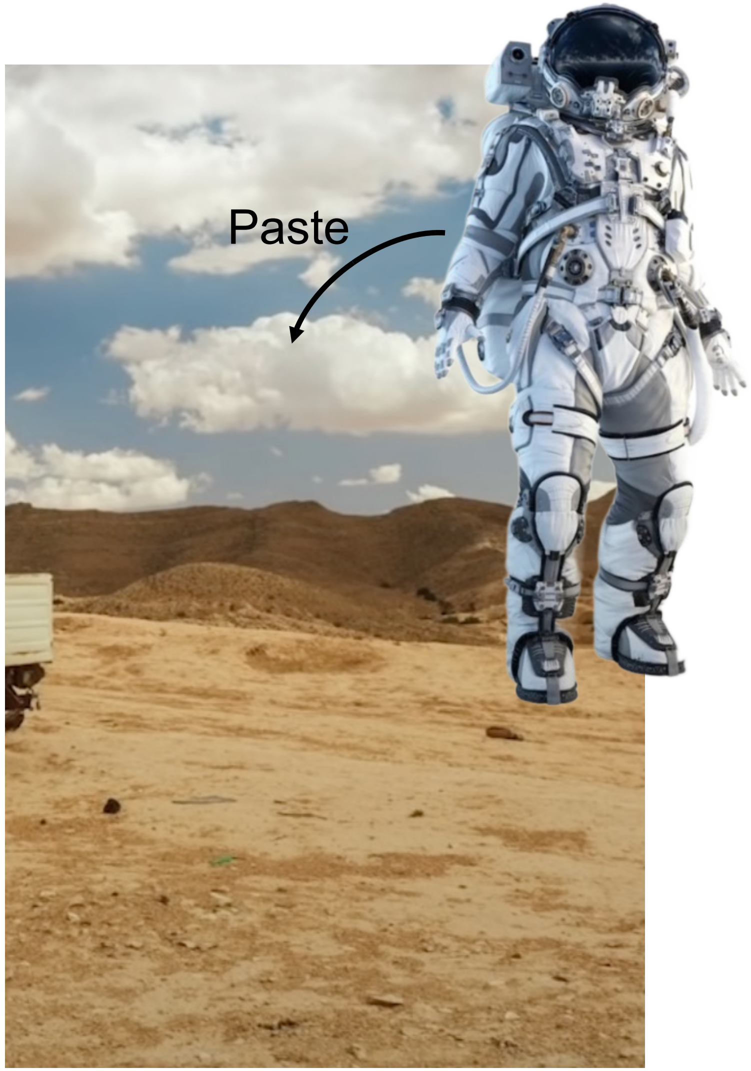






Harmonize

Image composition and harmonization

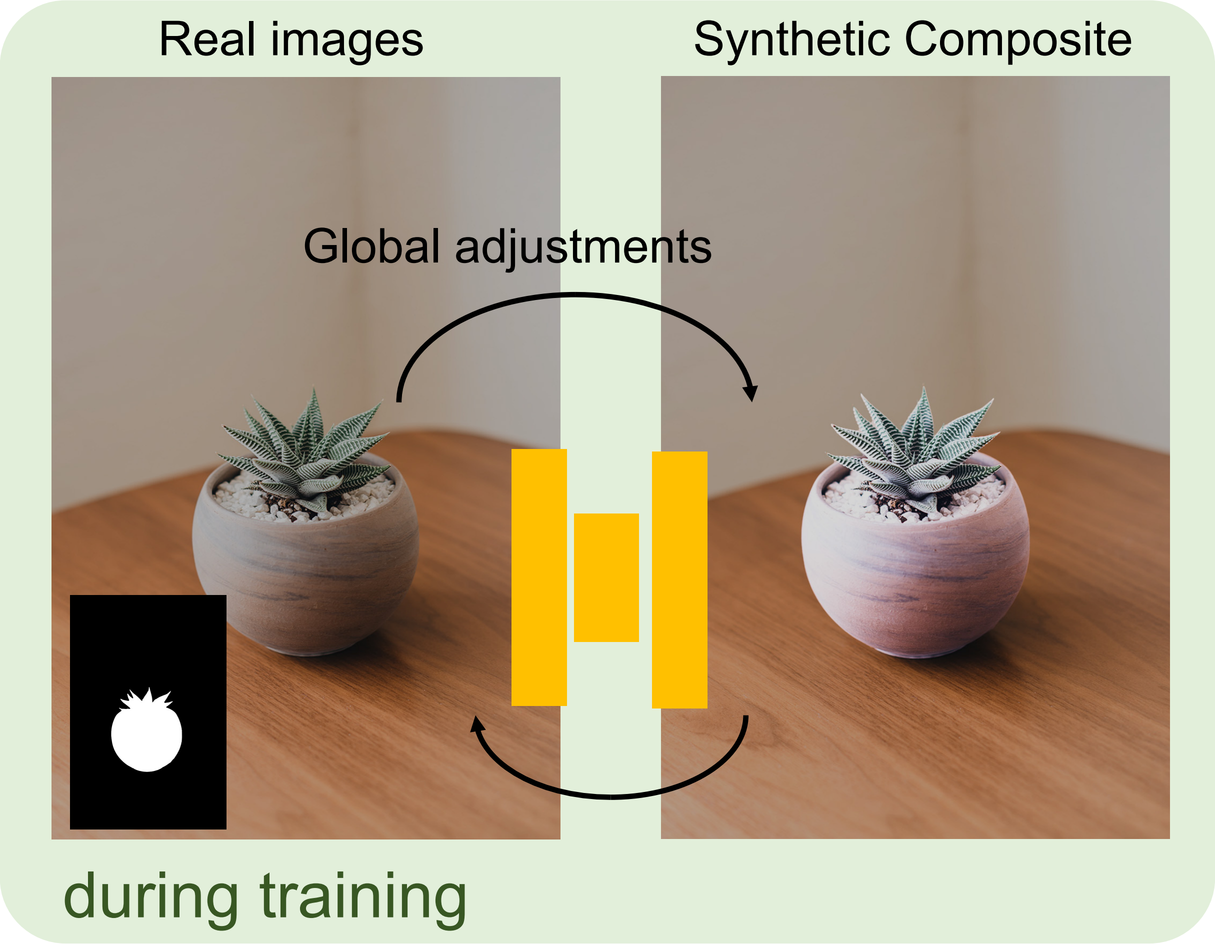


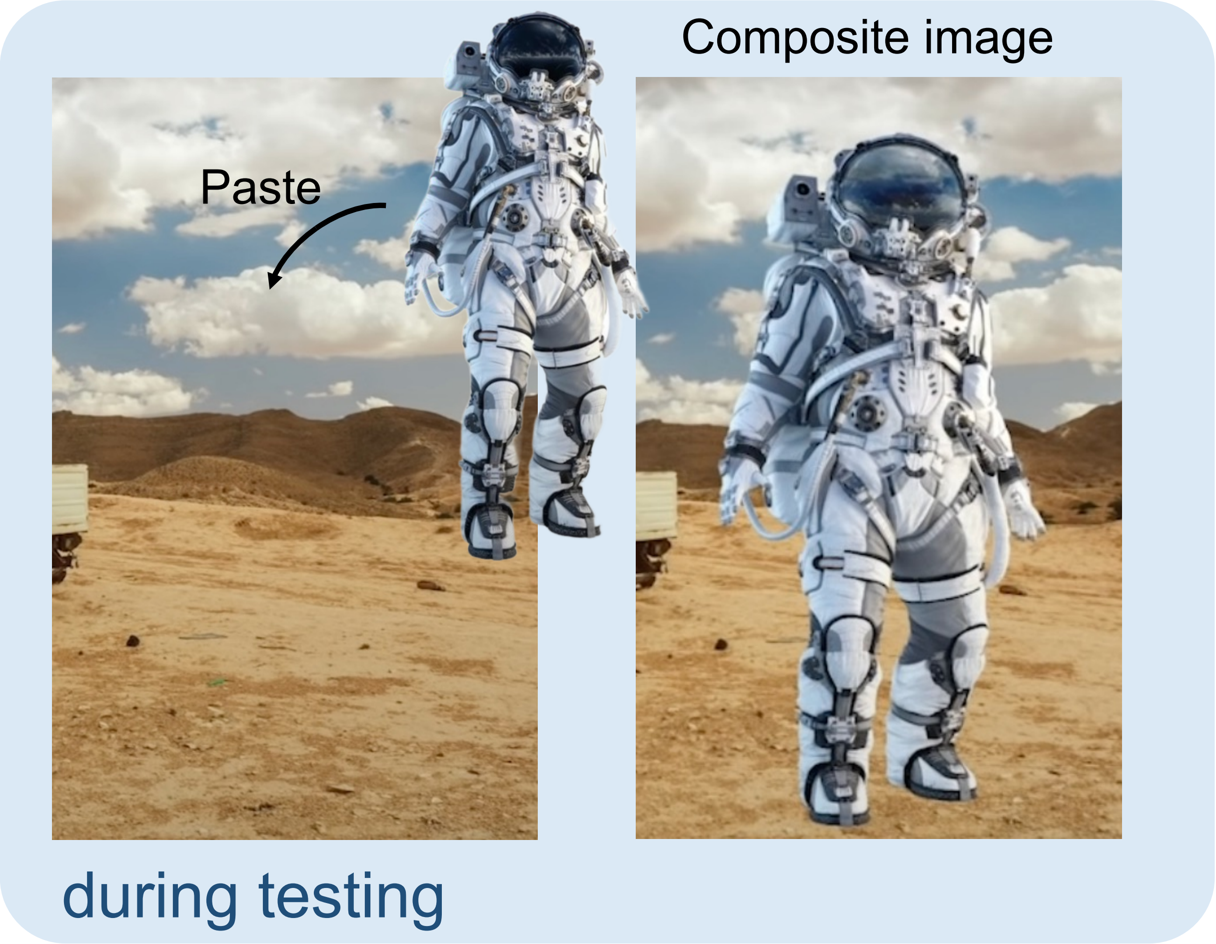
Composite image

Image
Harmonization

Harmonized image

Previous works:
Train harmonization from synthetic composites





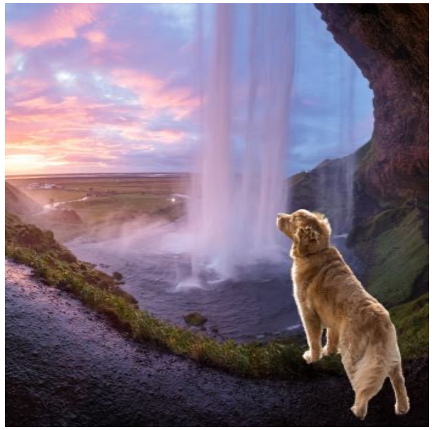
- Domain gaps between training and testing
- Only perform global harmonization

[1] Cong et al. 2022 [2] Ling et al. 2021 [3] Guo et al. 2021 [4] Cong et al. 2020 [5] Ke et al. 2022

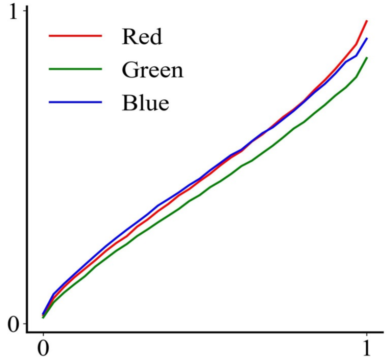
Our contributions

Semi-supervised Parametric Real-world image harmonization

- Bridge the domain gaps through training on **real composites**.
- High-res harmonization with **parametric controls (color and shading)**.
- First approach enables **local harmonization** (through shading map).

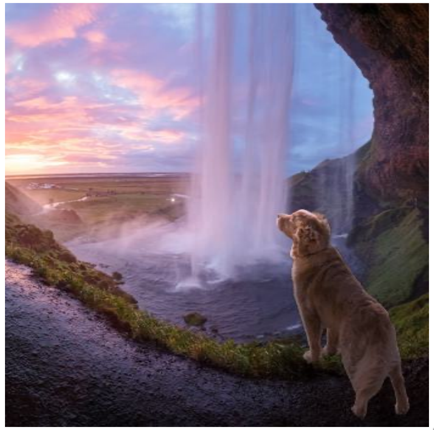


Input composite



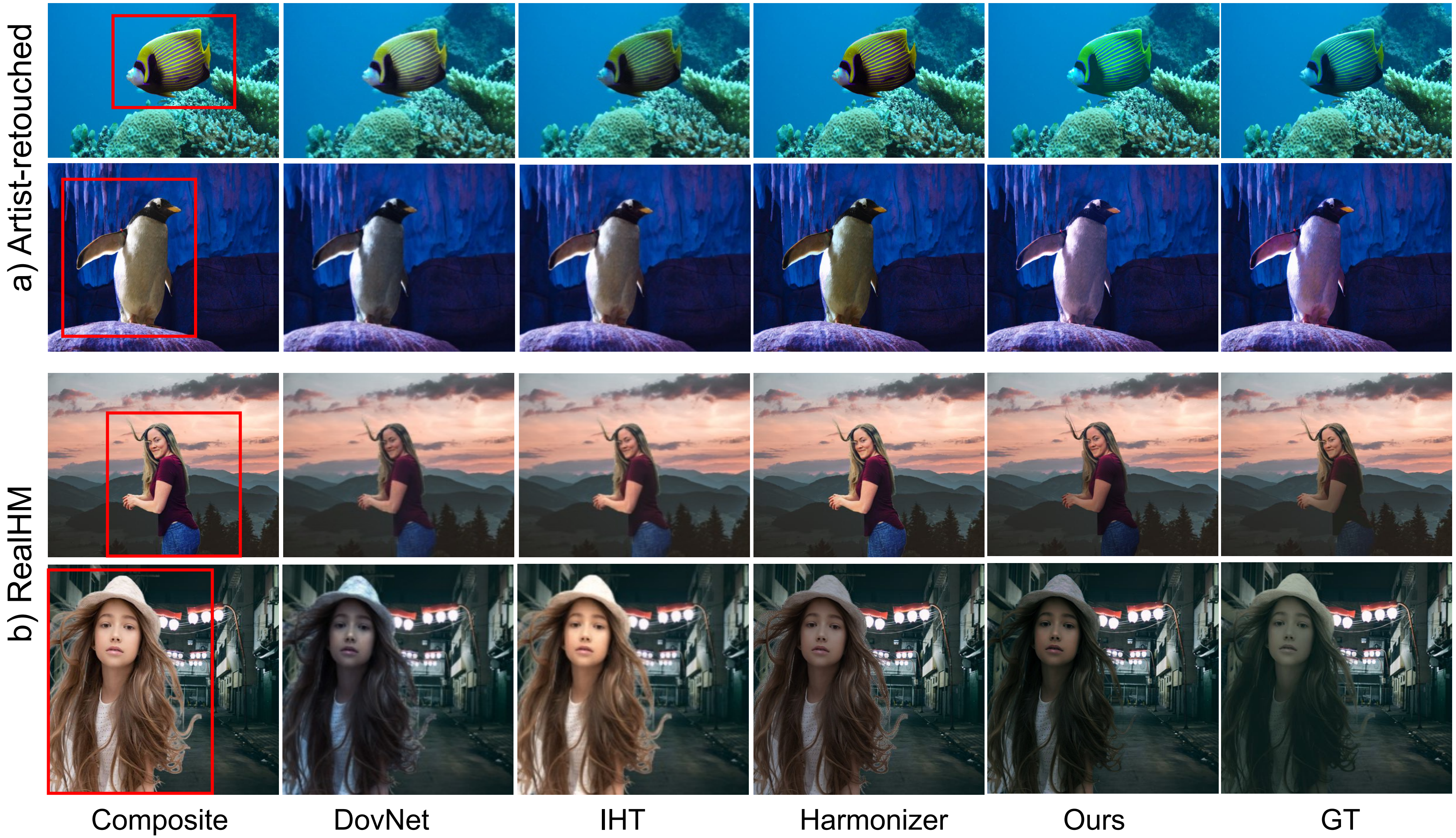
Color harmonization

Local shading



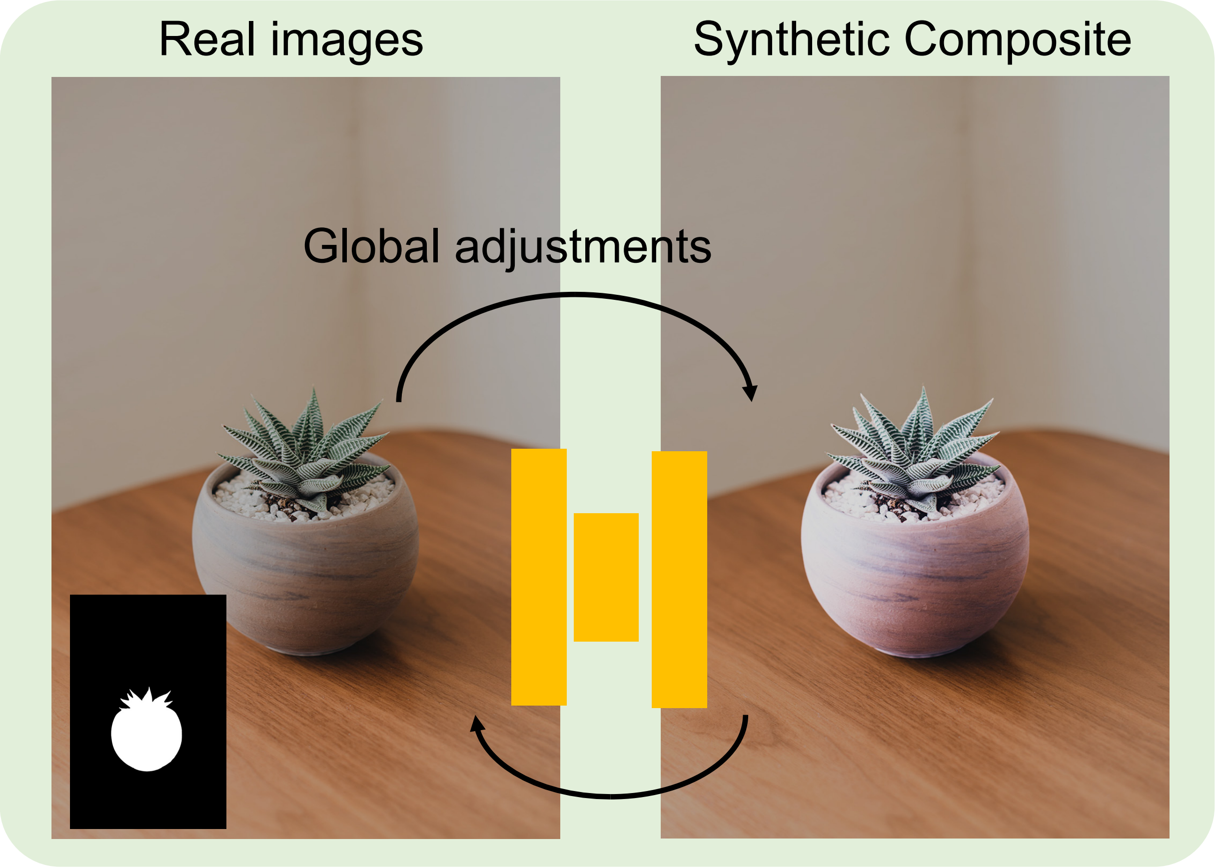
Harmonized results

Outperforms SOTA methods



[1] Cong et al. 2020 [2] Guo et al. 2021 [3] Ke et al. 2022

Why not training on synthetic composites



- Same foreground/background lighting, smooth boundary, consistent shading.
- Unnatural adjustments degrade harmonization performance.
- Only global harmonization. (e.g., color, luminosity)

Ours: learn image harmonization from **real composites.**

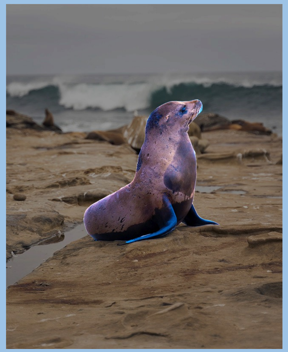
Dual-stream training strategy

Dual-stream training

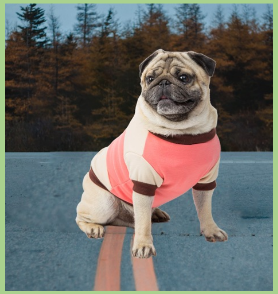
Sampled 50%

Sampled 50%

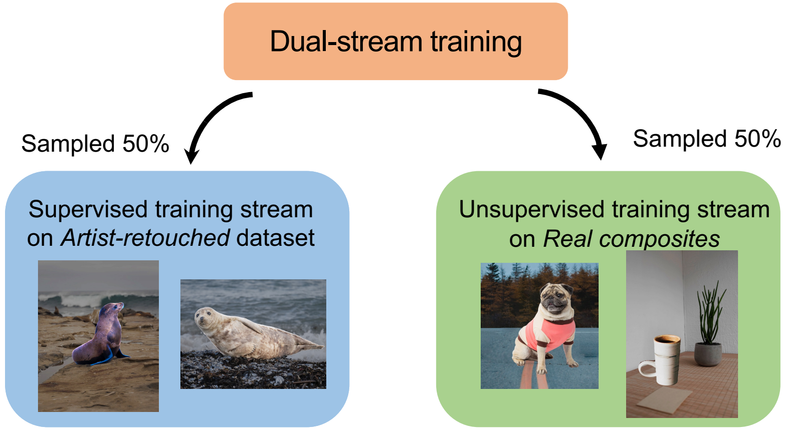
Supervised training stream
on *Artist-retouched* dataset

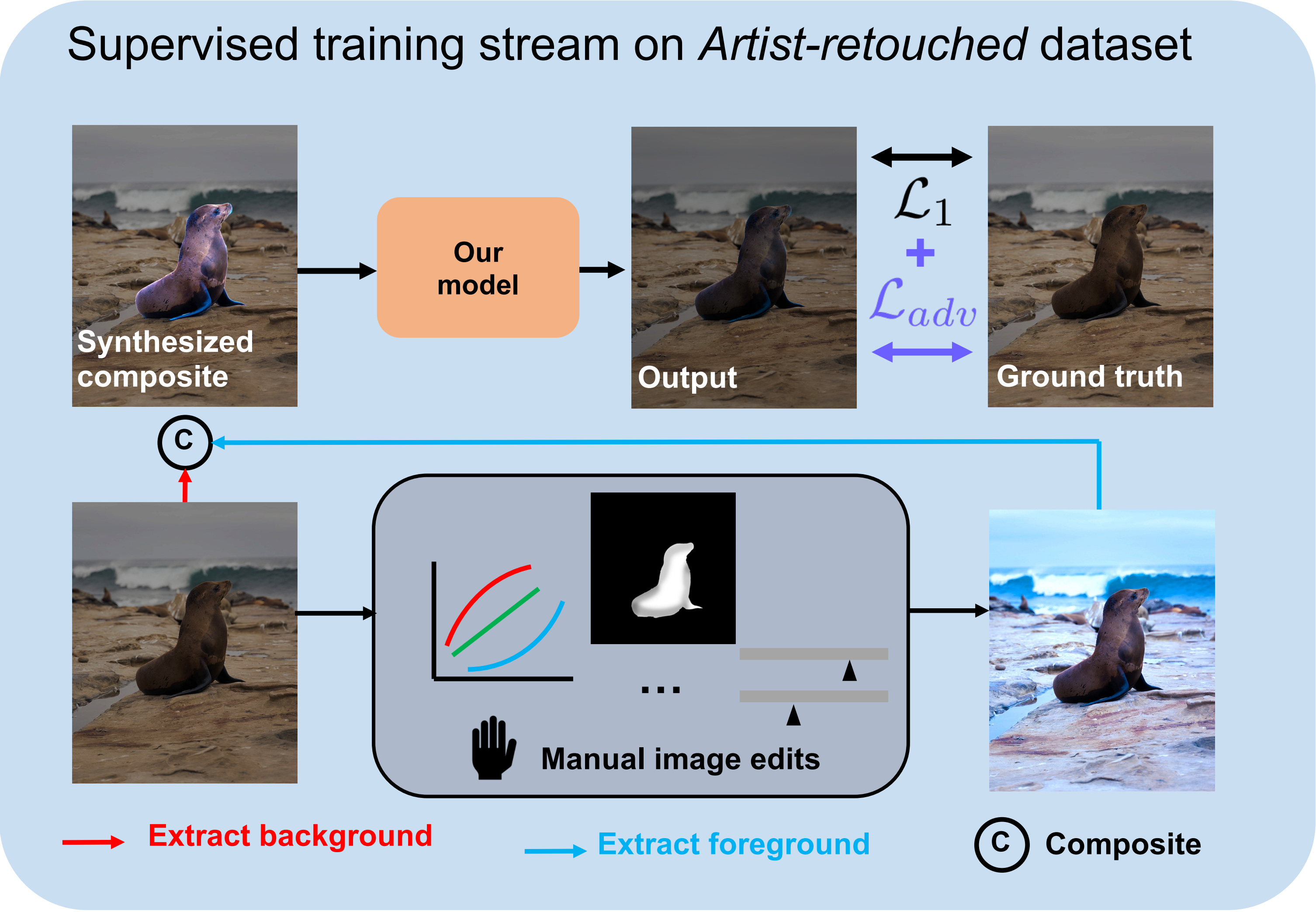


Unsupervised training stream
on *Real composites*



Supervised training stream





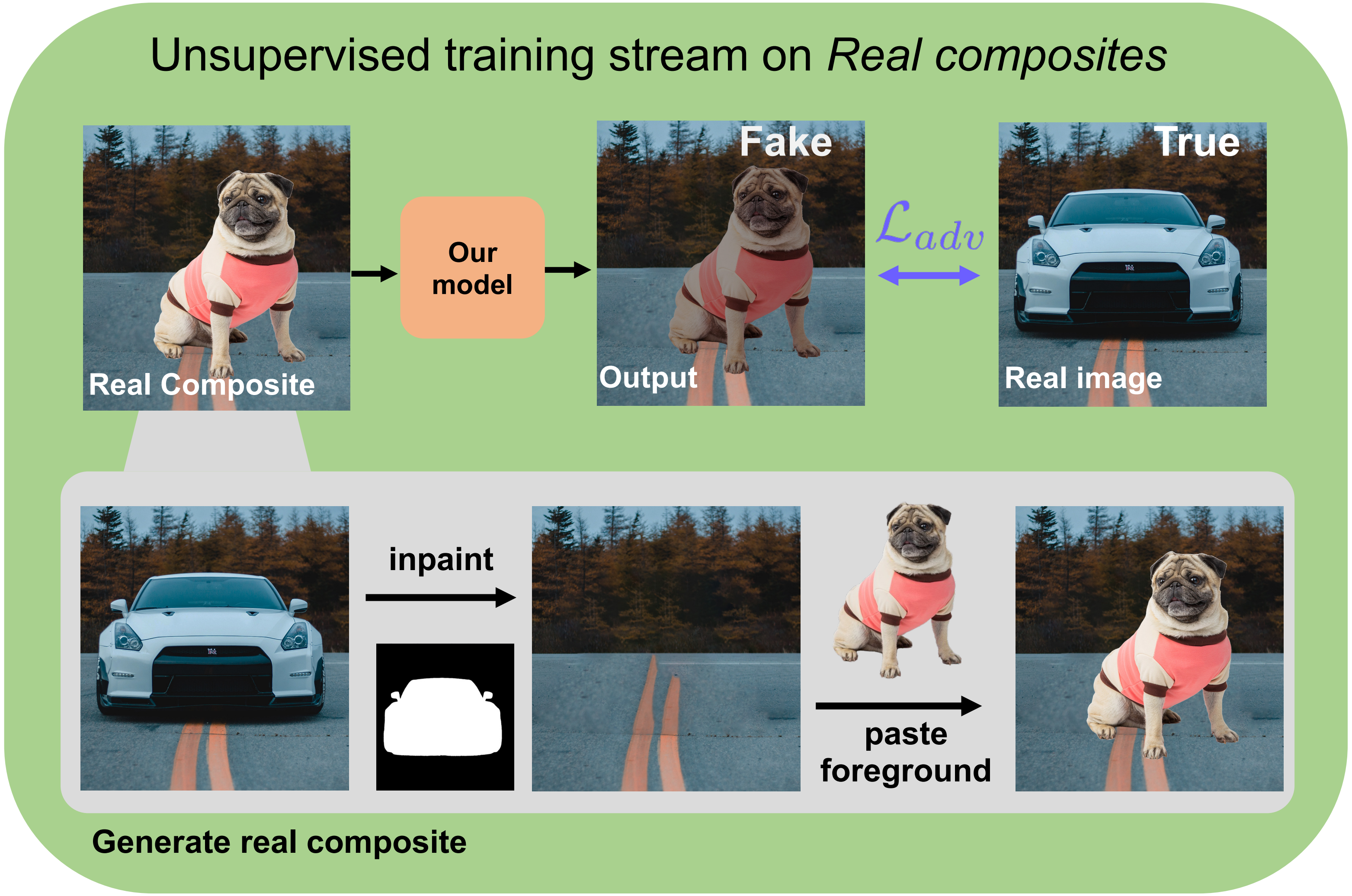
Previous works

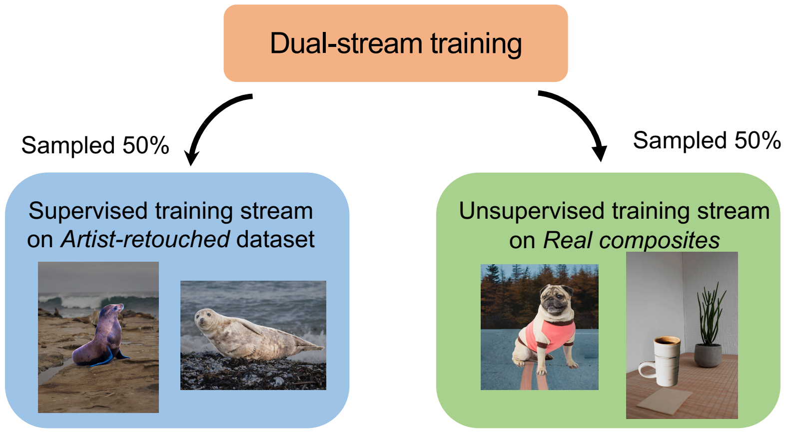
- Unnatural adjustments. ✗
- Only global adjustments. ✗

Ours

- Natural *Artist* adjustments. ✓
- Both global and local edits. ✓

Unsupervised training stream





Previous works

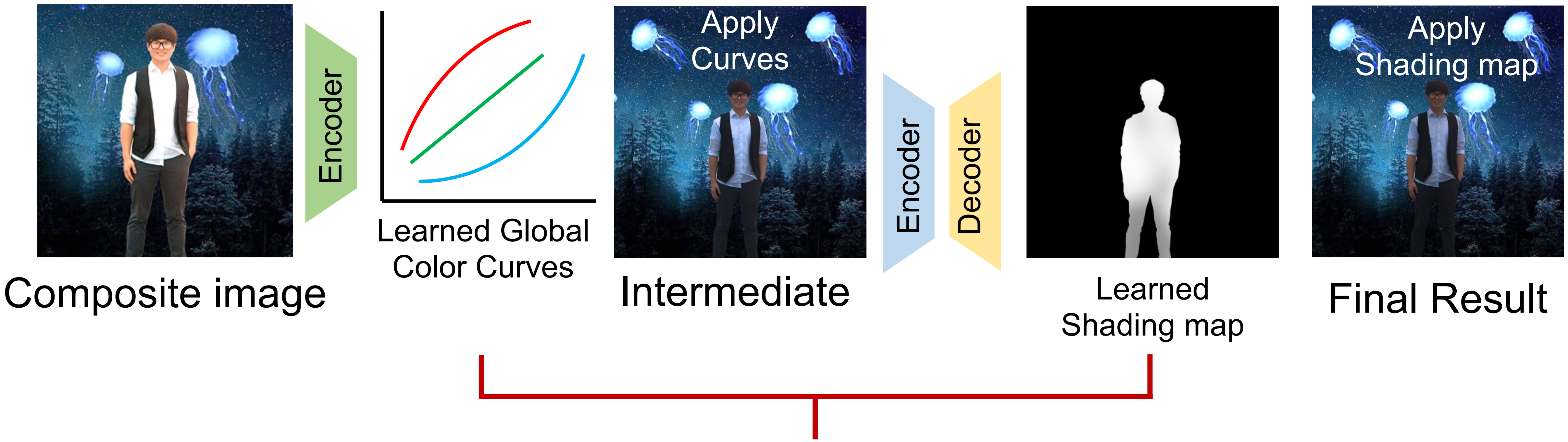
- Trained solely on synthetic composites. ✗

Ours

- Trained on both synthetic and real composites. ✓
- Bridge domain gaps and enable local harmonization. ✓

$\mathcal{L}_{adv}$ Is only adversarial loss enough?

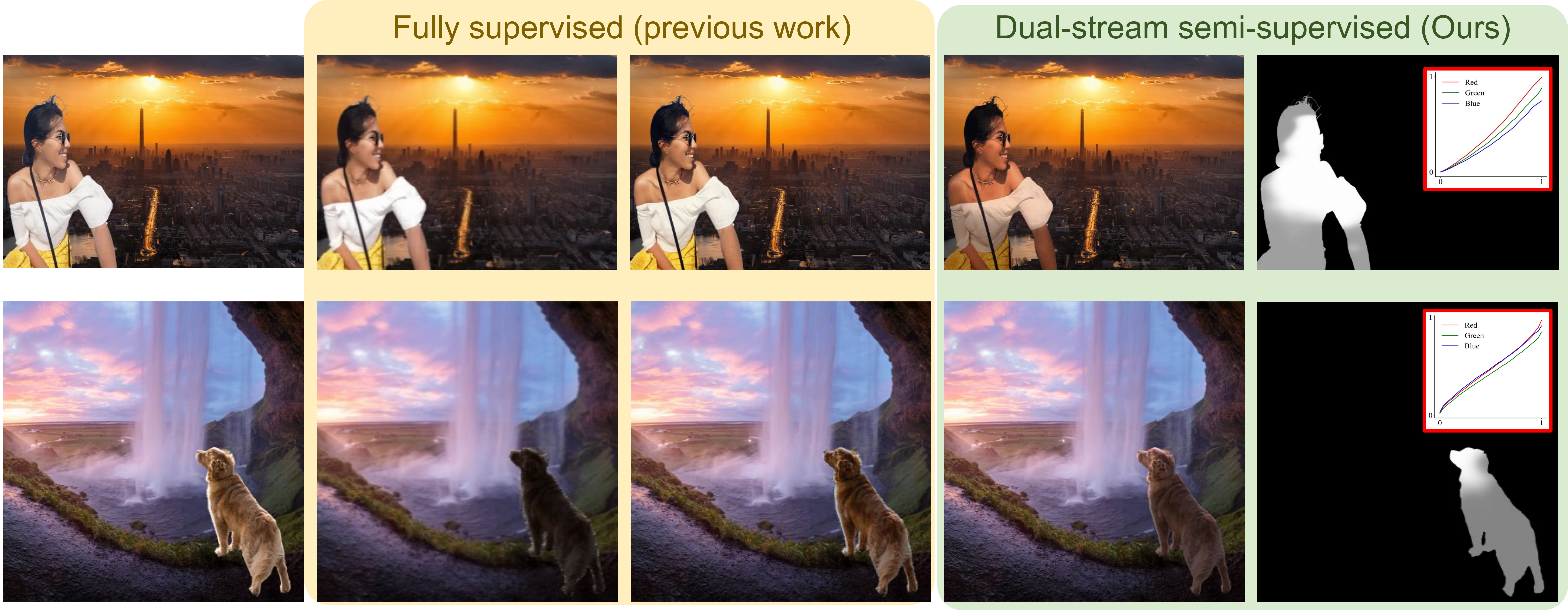
Parametric model regularizes adversarial training



1. Color curves and shading map can scale up to any resolution.

2. Provide user full parametric controls.

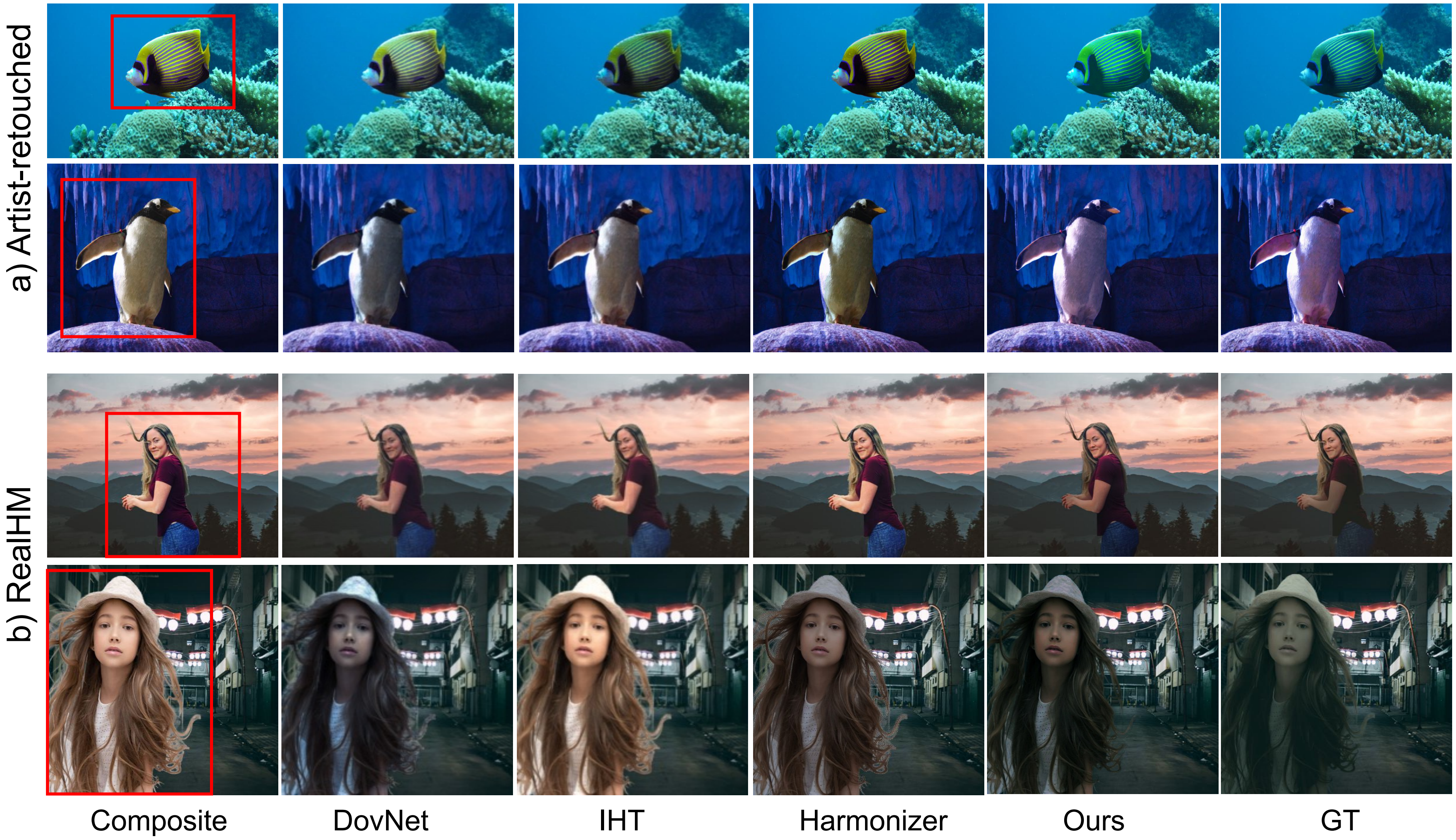
Visualization results on modeling local tonal changes



Composite | IHT | Harmonizer | **Ours** | Parametric curves & shading map

[1] Cong et al. 2020 [2] Guo et al. 2021 [3] Ke et al. 2022

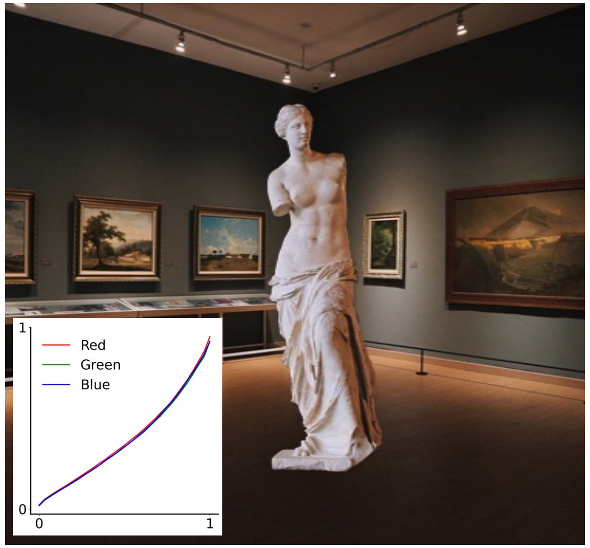
Better agreements with ground truth



[1] Cong et al. 2020 [2] Guo et al. 2021 [3] Ke et al. 2022

Visualization of parametric controls

Composite



Intermediate results
(global curves)

Shading map

Final results
(curves + shading map)

Quantitatively outperform SOTA methods

Dataset	Method	MSE	PSNR	SSIM $\times 10^{-2}$	LPIPS $\times 10^{-3}$
Artist-Retouched dataset	Composite	603.2	23.41	91.19	40.18
	DovNet	352.4	26.42	90.83	56.47
	IHT	369.3	26.36	90.87	55.80
	Harmonizer	239.1	29.42	93.84	33.75
	Ours	**170.1**	**29.79**	**94.56**	**29.18**
RealHM	Composite	404.4	25.88	94.70	29.32
	DovNet	225.1	26.72	92.00	47.50
	IHT	264.0	26.48	92.46	48.48
	Harmonizer	231.4	27.40	94.86	27.62
	Ours	**153.3**	**28.34**	**95.51**	**23.09**

Metric comparisons

Methods	B-T score
Composite	0.1025
DovNet	0.1342
IHT	0.2350
Harmonizer	0.2257
Ours	**0.3025**

User study results

Demo – parametric controls enable **Creativities!**

Conclusions

Semi-supervised Parametric Real-world image harmonization

- Bridge the domain gap through training on **real composites**.
- First approach enables **local harmonization** (through shading map).
- High-res harmonization with **parametric controls (color and shading)**.
- Outperform SOTA methods both quantitatively and qualitatively.

Thanks for your attention!

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