INTERNATIONAL CONFERENCE
ON COMPUTATIONAL PHOTOGRAPHY 2022
August 1-3, Caltech, Pasadena

Time-of-Day Neural Style Transfer for Architectural Photographs

Yingshu Chen[1] Tuan-Anh Vu[1] Ka-Chun Shum[1] Binh-Son Hua[2] Sai-Kit Yeung[1]

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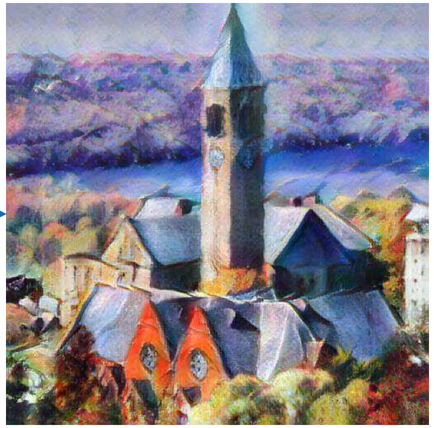
Motivation

Style Transfer

Artistic style transfer[1]



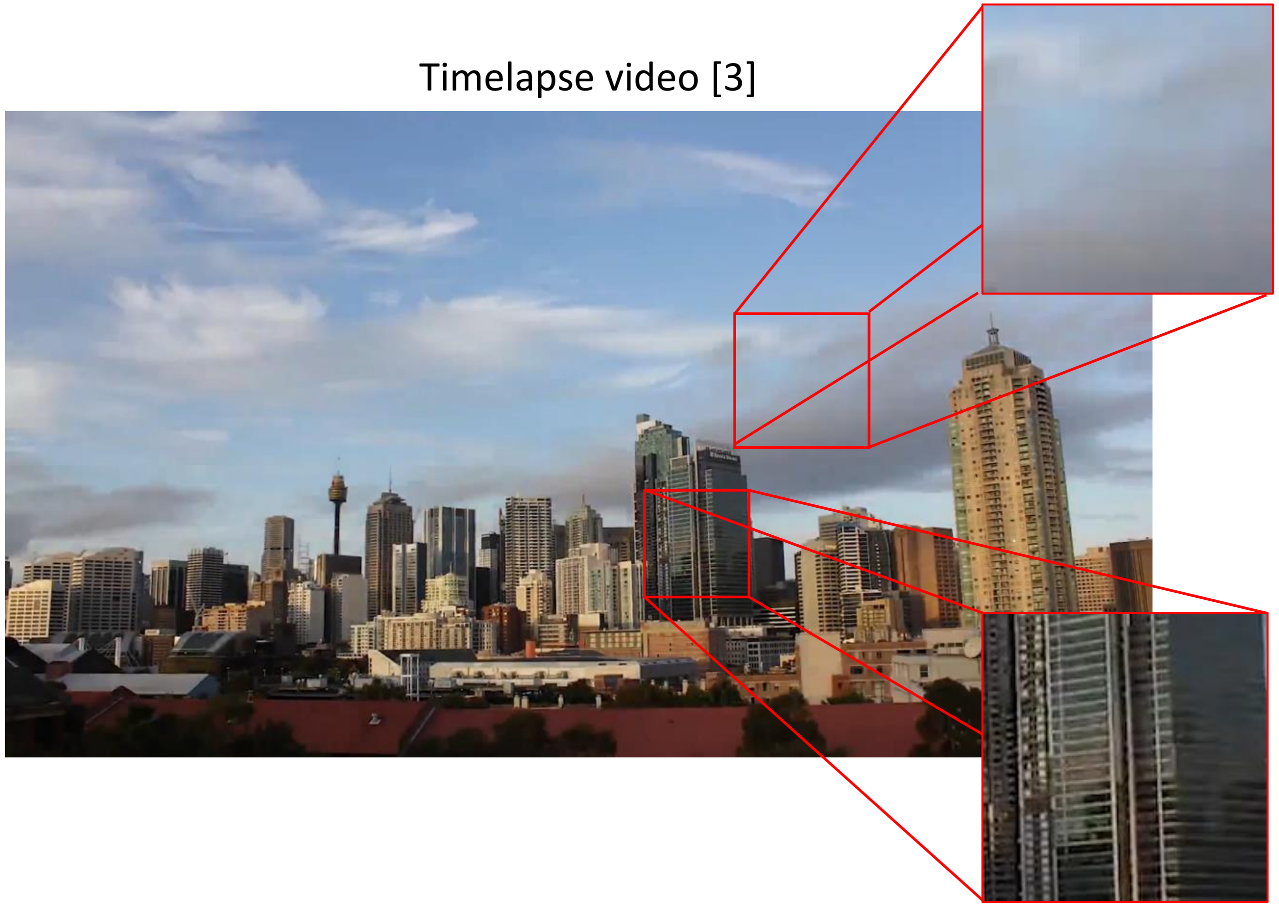
Domain translation[2]

Examples from
[1] Huang and Belongie, “Arbitrary style transfer in real-time with adaptive instance normalization”, ICCV 2017.
[2] Chang et al., “Domain-specific mappings for generative adversarial style transfer”, ECCV 2020.

Motivation

- ***Architectural photography style transfer*** is challenging due to its special composition of dynamic sky and static foreground.

Timelapse video [3]



Video from
[1] Shih, et al. "Data-driven hallucination of different times of day from a single outdoor photo." Siggraph Asia 2013.

Motivation

- ***Architectural photography style transfer*** is challenging due to its special composition of dynamic sky and static foreground.
- Generic neural style transfer and image-to-image translation treat the image as a single entity without knowing the foreground and background:
  - Destroy geometric features of the original architecture.
  - Lead to mismatched chrominance

content & style

distorted geometry, mismatched color

correct geometry, correct semantic style (Ours)

[2] Huang and Belongie, “Arbitrary style transfer in real-time with adaptive instance normalization”, ICCV 2017.
[3] Chang et al., “Domain-specific mappings for generative adversarial style transfer”, ECCV 2020.
Input images from pexels.com, 4147341 and pikwizard, 074a69d48e93c913aa718a929aea3b96.
Style images from unsplash.com, K4bvYKfXi3w and by *Ed Lofdahl* .

Motivation

- ***Architectural photography style transfer*** is challenging due to its special composition of dynamic sky and static foreground.
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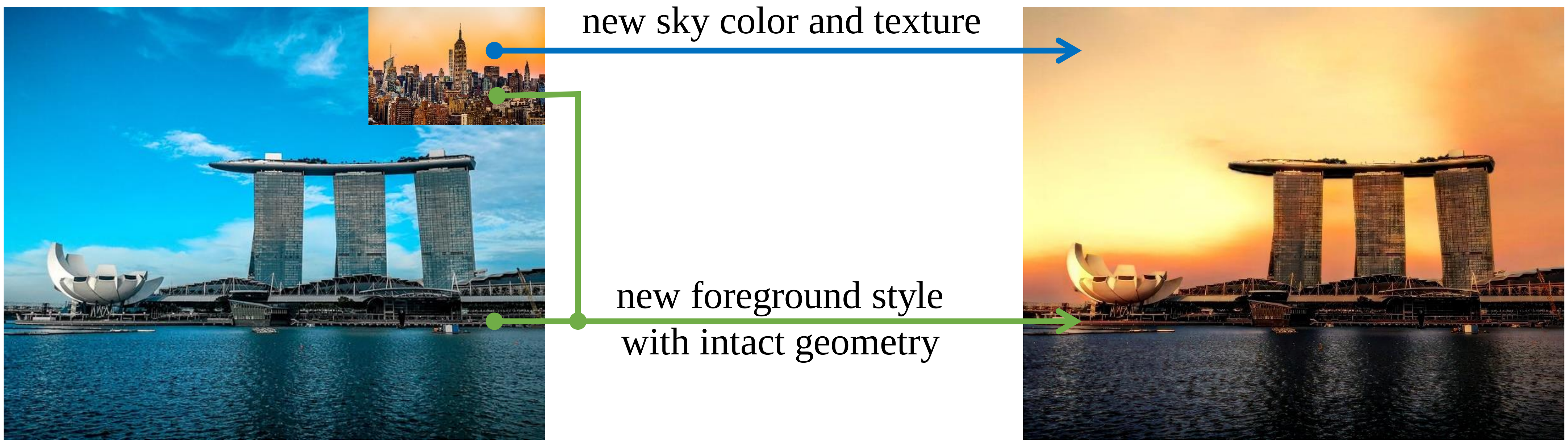
Problem Overview

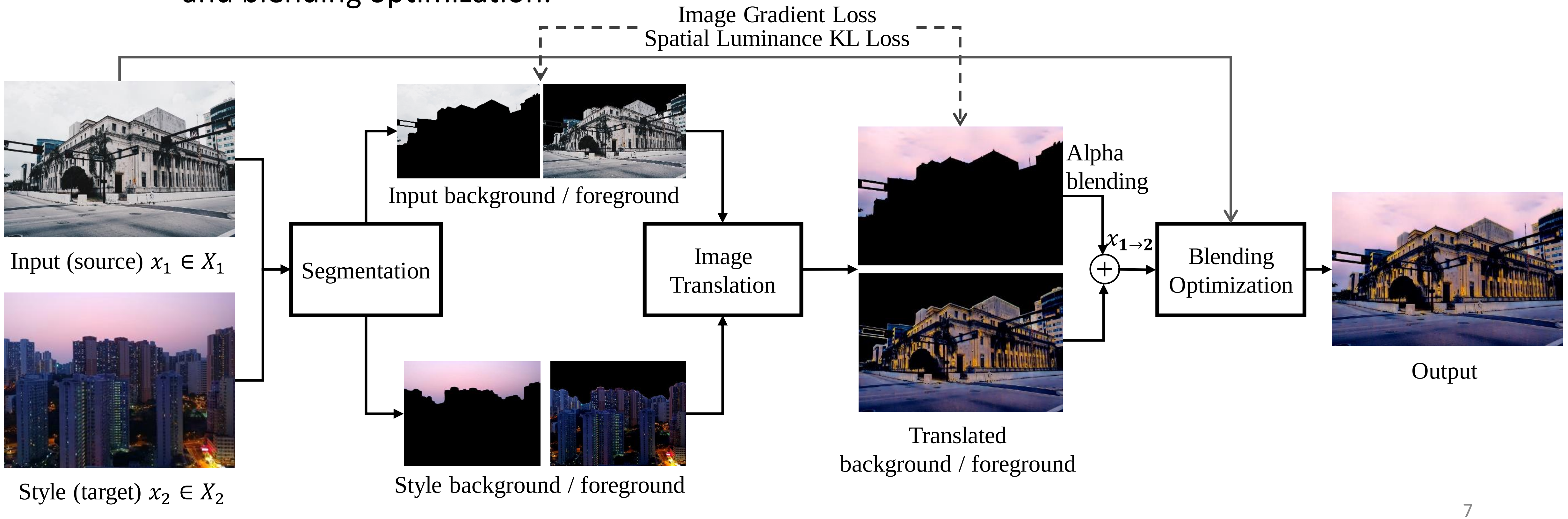
- Architectural Photo Style Transfer:
  - Given an architectural photo and a style reference, we transfer styles of background and foreground separately while keeping foreground geometry intact.



Input images from unsplash.com, Ncmd8uLe8H0 and unsplash.com, 5omwAMDxmkU.

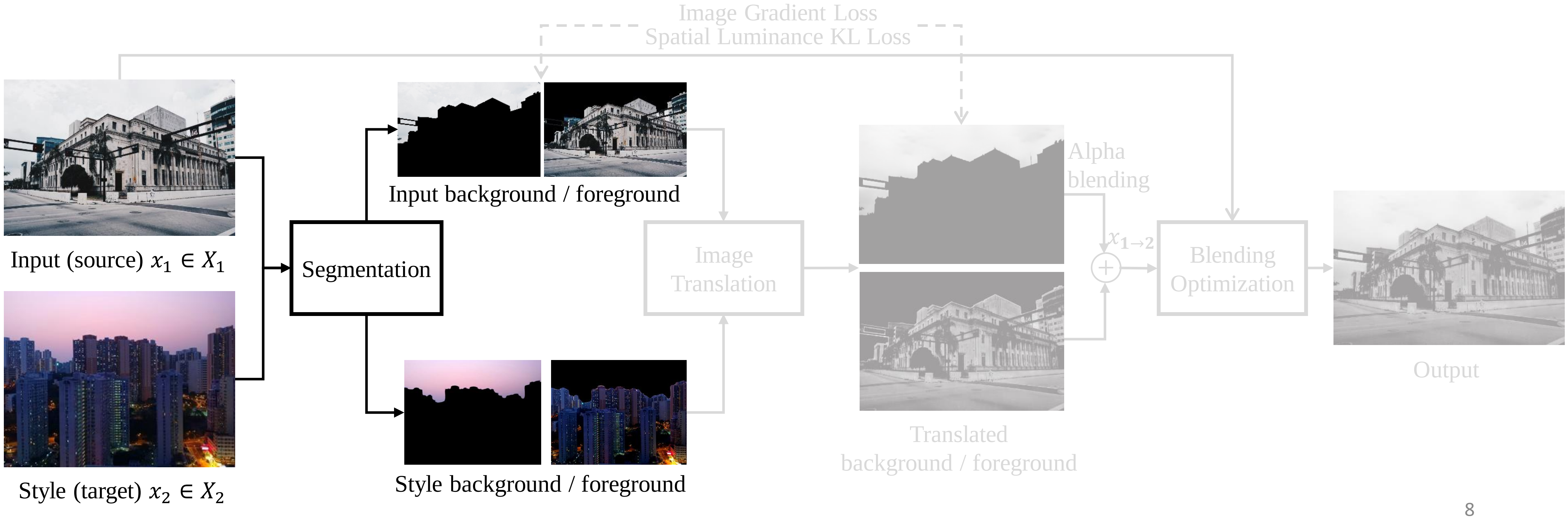
Methodology

- Overview
  - Architectural style transfer framework with three modules: segmentation, image translation and blending optimization.



Methodology

- Step 1 - Segmentation
  - Explicitly represent foreground and background of source and style images.



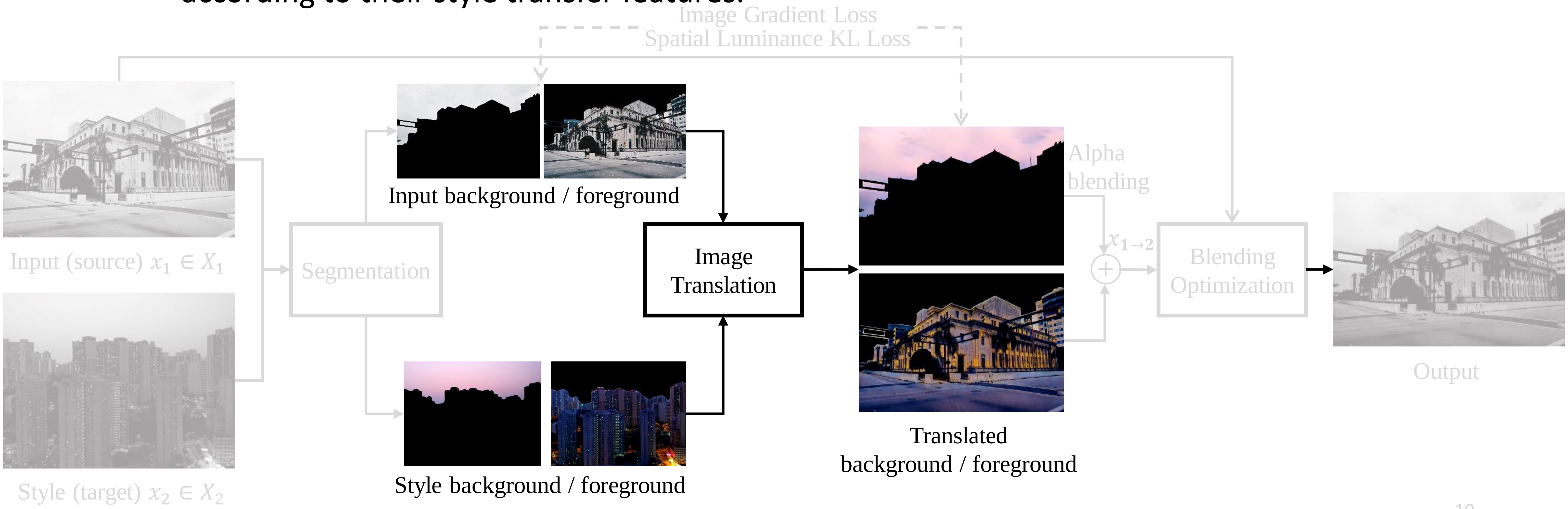
Methodology

- Segmentation
  - Disentangle foreground and background for style transfer.
  - Foreground contains architecture, street, etc.
  - Background contains sky.
  - Use pretrained model (training stage) or manual labeling.

Input image from pikwizard, 9cda9a1396248a477dce3fd81baad5e9.
Style image from pexels.com, city-buildings-1904605.

Methodology

- Step 2 – Image Translation
  - Train foreground and background translation models with different training hyperparameters according to their style transfer features.



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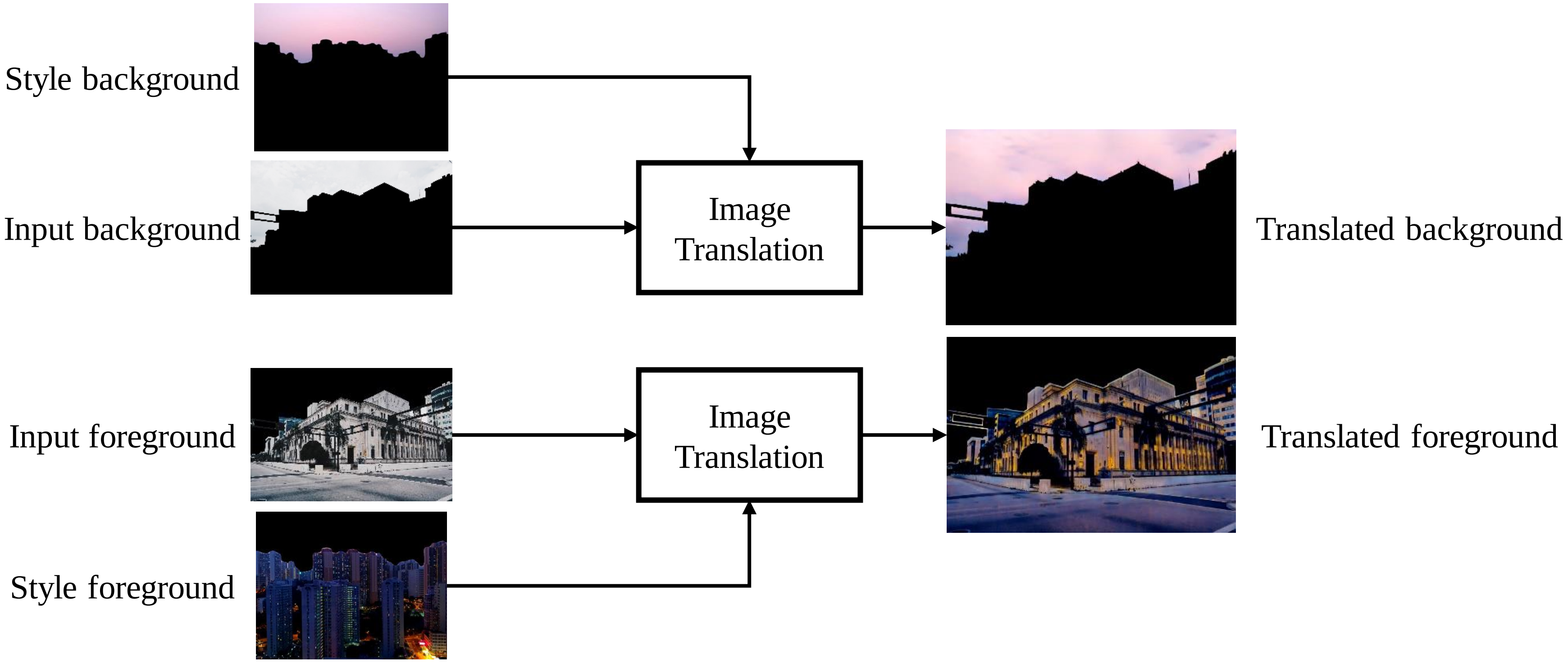
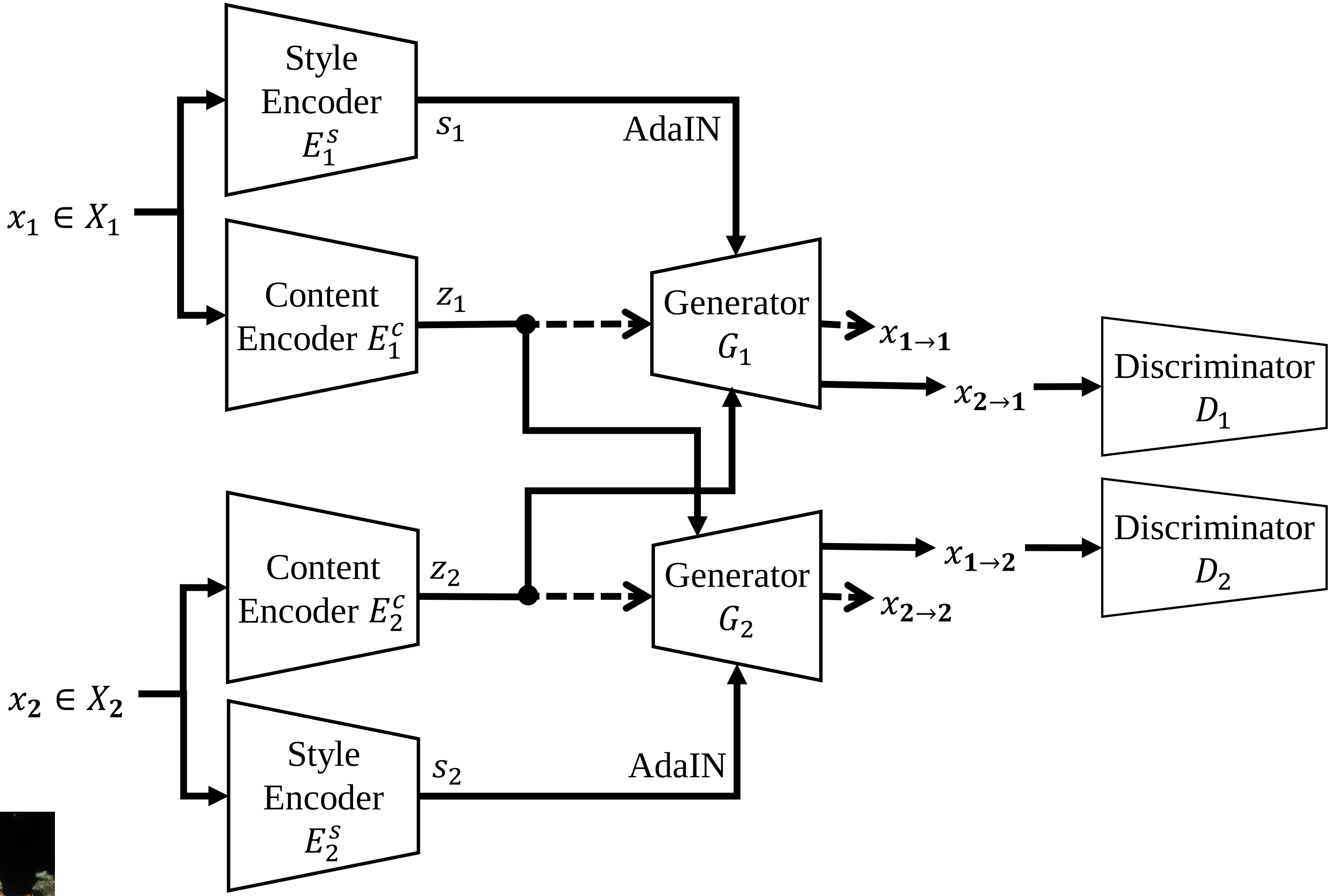


Methodology

- Image Translation
  - Bidirectional image-to-image translation for unpaired data.
  - Reconstruction, cycle-consistency, adversarial losses.

Fail to preserve primal geometry



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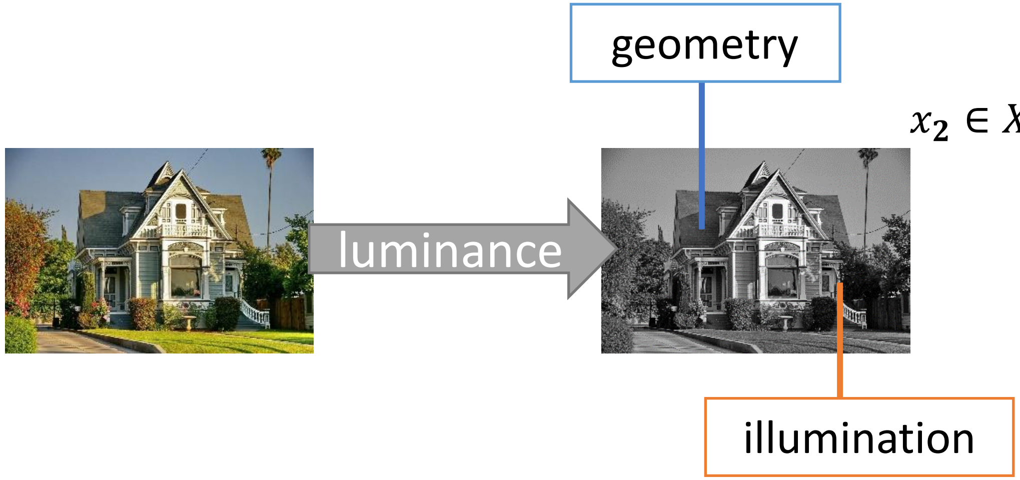
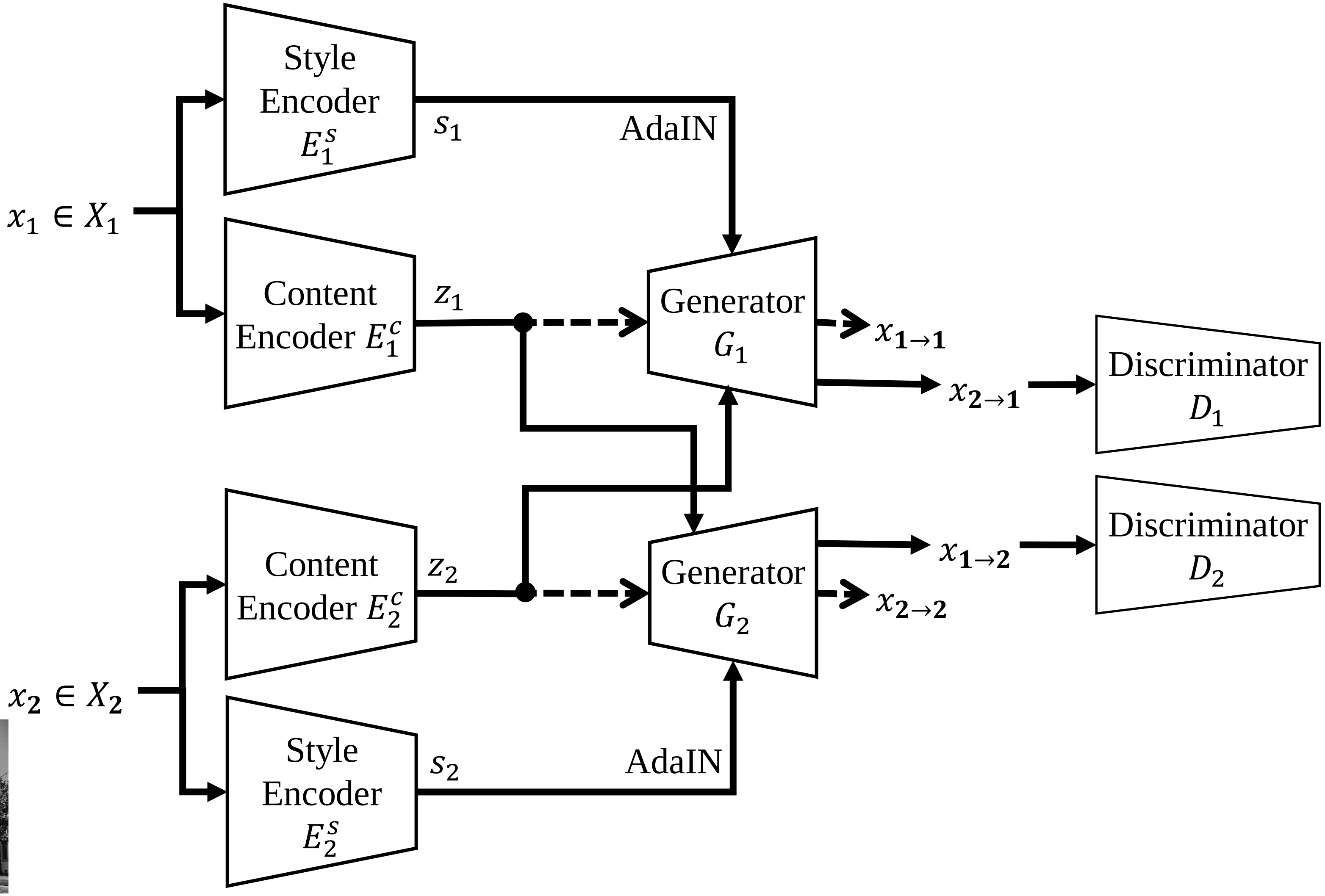
Input image from pikwizard, 074a69d48e93c913aa718a929aea3b96.

Methodology

- Image Translation
  - Bidirectional image-to-image translation for unpaired data.
  - Reconstruction, cycle-consistency, adversarial losses.
  - High-frequency geometry preservation.





Input image from pikwizard, 074a69d48e93c913aa718a929aea3b96.

Methodology

- Image Translation
  - Bidirectional image-to-image translation for unpaired data.
  - Reconstruction, cycle-consistency, adversarial losses.
  - High-frequency geometry preservation.

High-frequency geometry losses:

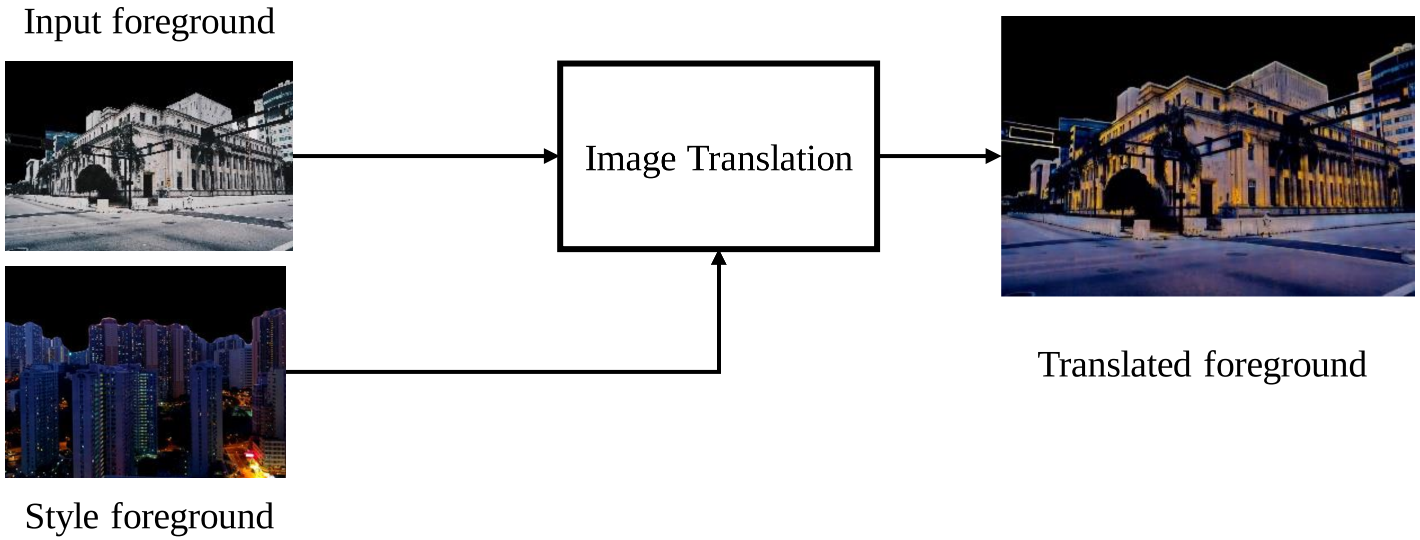
- Image Gradient loss:

$$\mathcal{L}_{gd} = \mathbb{E}_{x_1,x_2}[\|\nabla(Y(x_{1\to2}) - \nabla(Y(x_1)\|_1]$$

- Spatial luminance KL loss:

$$\mathcal{L}_{kl} = \mathbb{E}_{x_1,x_2}[KL(Y(x_{1\to2})\|Y(x_1))]$$

$Y(\cdot)$ is luminance channel.



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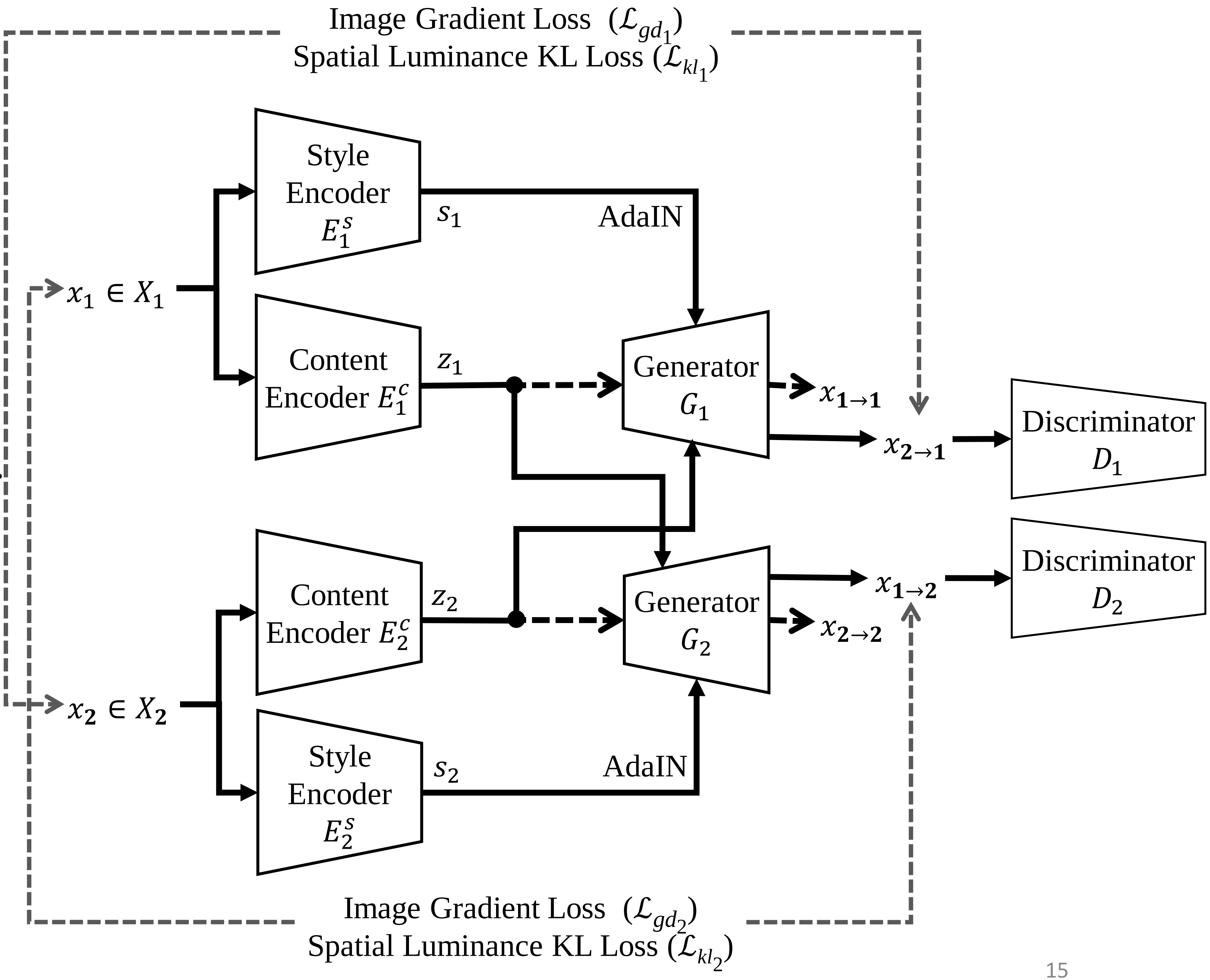
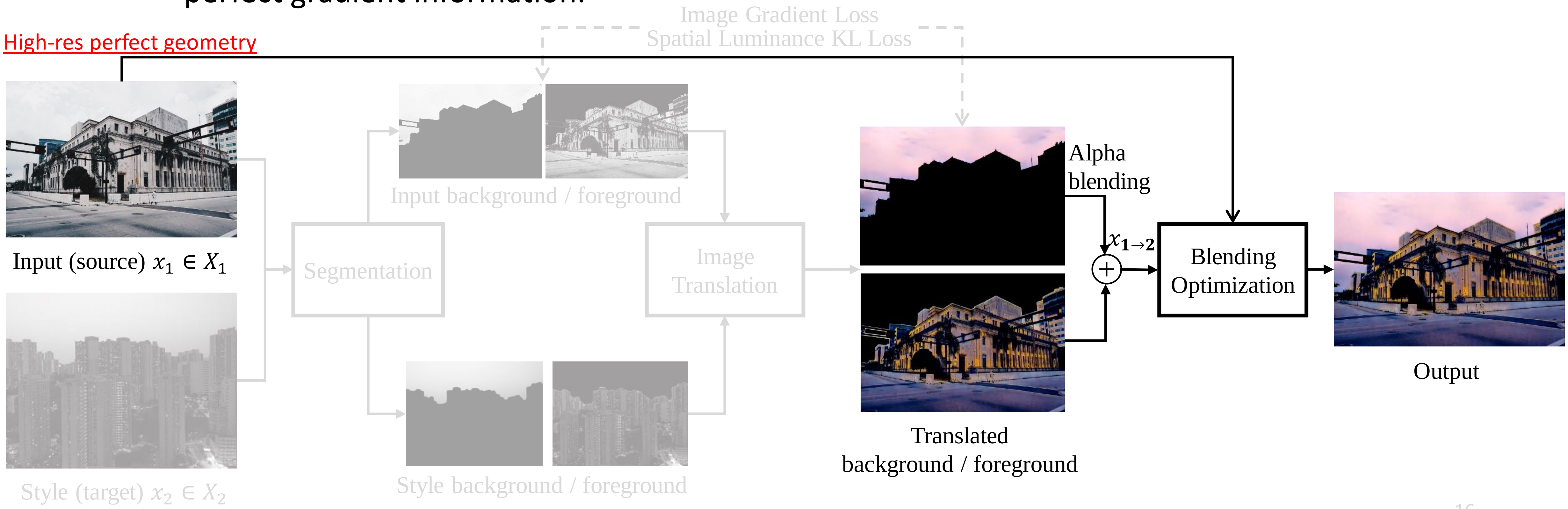


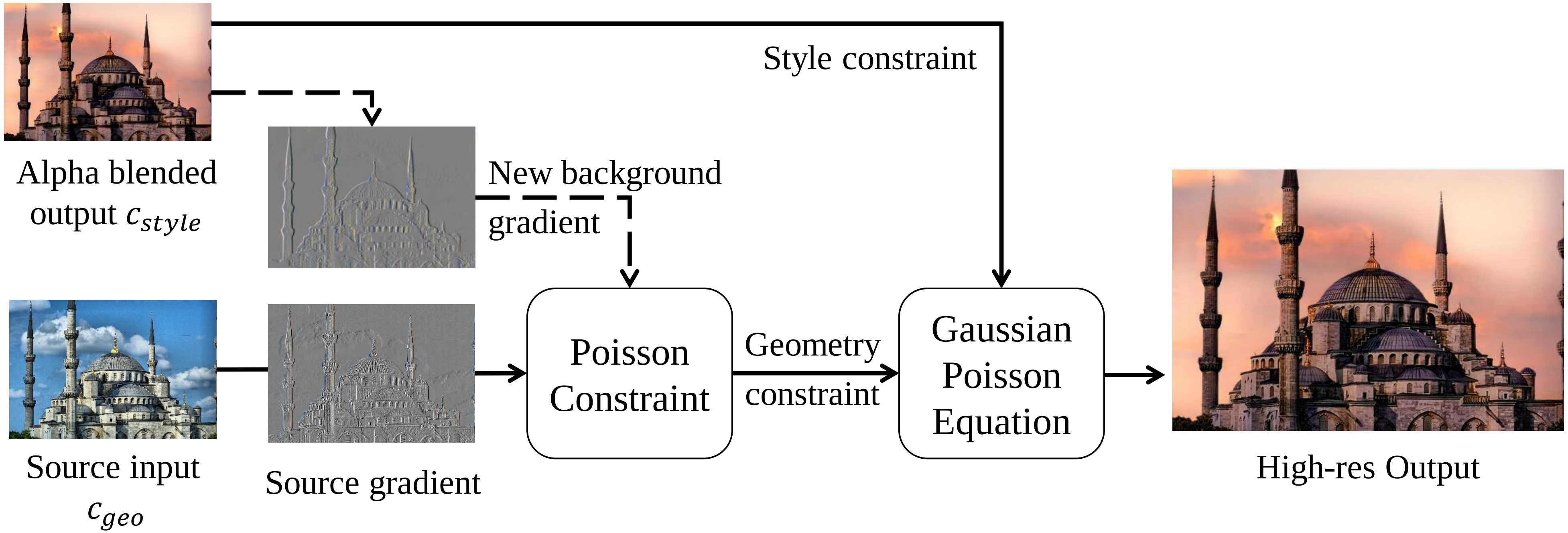
Methodology

- Step 3 – Blending Optimization
  - With input high-resolution source geometry information, we optimize blended results with perfect gradient information.



Methodology

- Blending Optimization
  - Restore high-fidelity gradient information of input content.
  - Optional: new background sky texture gradient.

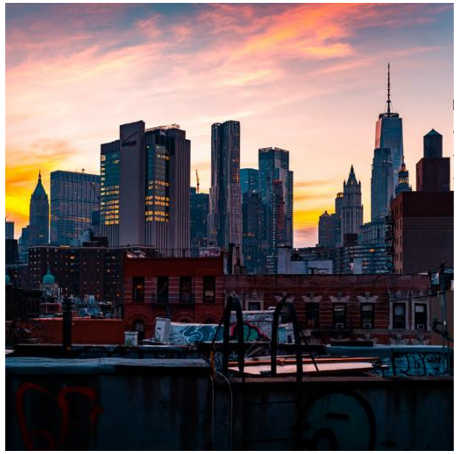


[4] Wu et al., “GP-GAN: Towards realistic high-resolution image blending,” ACMMM 2019.
Source image by David Spender.

Dataset

- Unpaired dataset from the Internet and time-lapse video frames.
- 21,000 architectural photos for training.
- 1,000 photos for evaluation.
- 4 labels for time-of-day styles: *day*, *golden*, *blue*, *night*, with diverse styles of architectures and sky.


day


golden


blue


night

Photos by Unsplash users *lisanto_12, bartmynameisbart, lanceanderson, christopher__burns*.

Experiments

- Ablation study
    - Segmentation

	e-SSIM↑	Acc↑	IS↑	IoU↑
Ours-whole	0.6838	0.8282	2.5240	0.7410
Ours	0.6359	0.9486	2.7290	0.7257

Ours-whole: our translation model trained with whole images.

Input source and style reference

Ours without segmentation

Ours with segmentation

Input image from unsplash.com, Zr-ZnTNekEY. Style image from unsplash.com, sw_ePW1sYnU.
*e-SSIM: SSIM on image edges.

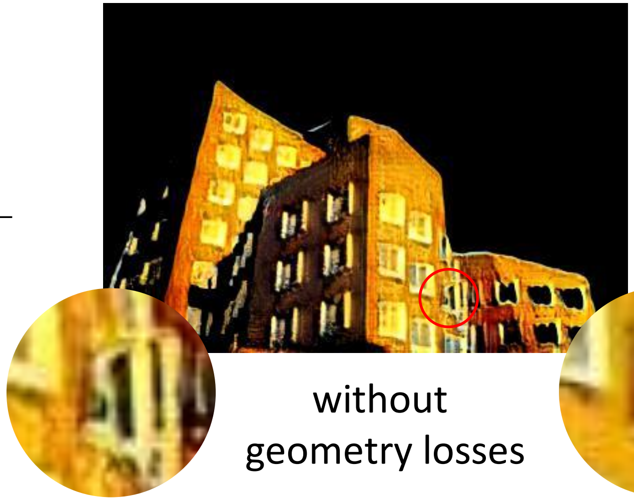
Experiments

- Ablation study
  - Geometry Losses

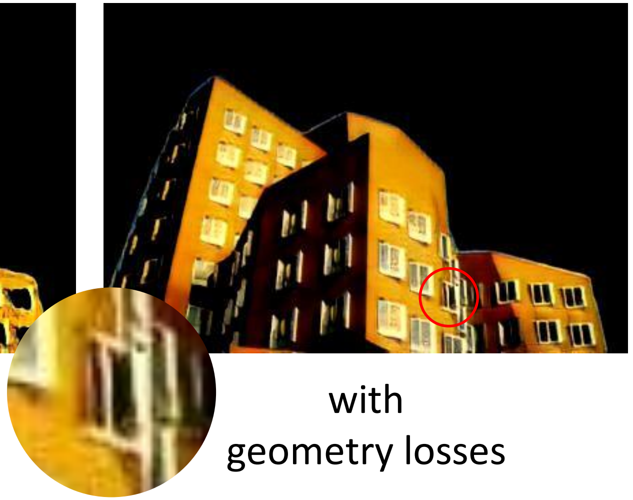
	w/o $\mathcal{L}_{kl} + \mathcal{L}_{gd}$	w/o $\mathcal{L}_{kl}$	w/o $\mathcal{L}_{gd}$	$\mathcal{L}_{total}$
e-SSIM↑	0.4800	0.5539	0.5159	**0.6359**
Acc↑	0.8934	0.9201	0.9265	**0.9486**
IS↑	2.6858	2.7183	2.7241	**2.7290**
IoU↑	0.6056	0.6536	0.6612	**0.7257**

$\mathcal{L}_{kl}$: spatial luminance KL loss.
$\mathcal{L}_{gd}$: image gradient loss.
$\mathcal{L}_{total}$: all losses.

Input source and style reference



without geometry losses



with geometry losses

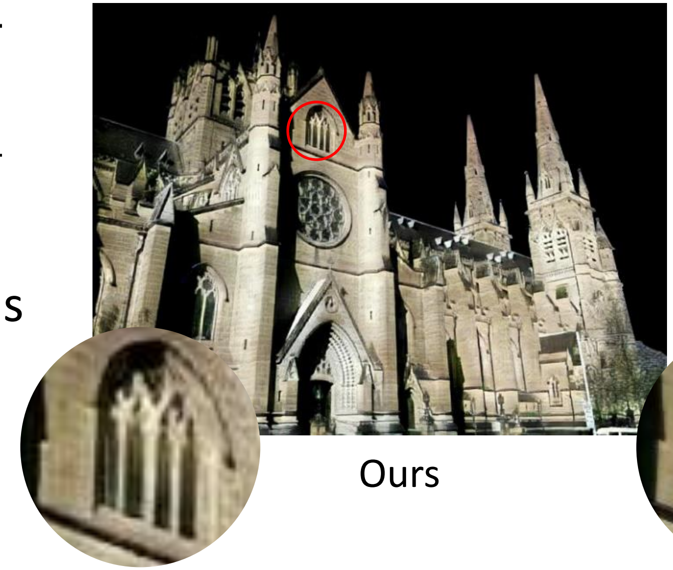
Only taking foreground as an example. Original image from unsplash,3onN7CKCrH8.
*e-SSIM: SSIM on image edges.

Experiments

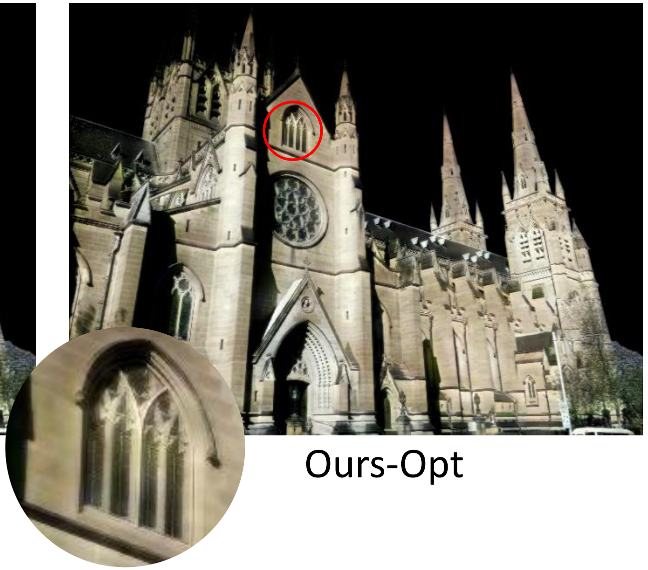
- Ablation study
  - Blending Optimization

	e-SSIM↑	Acc↑	IS↑	IoU↑
Ours	0.6359	0.9486	2.7290	0.7257
Ours-opt	$\boxed{0.8094}$	0.9007	2.6127	$\boxed{0.7715}$

Input source and style reference



Ours



Ours-Opt

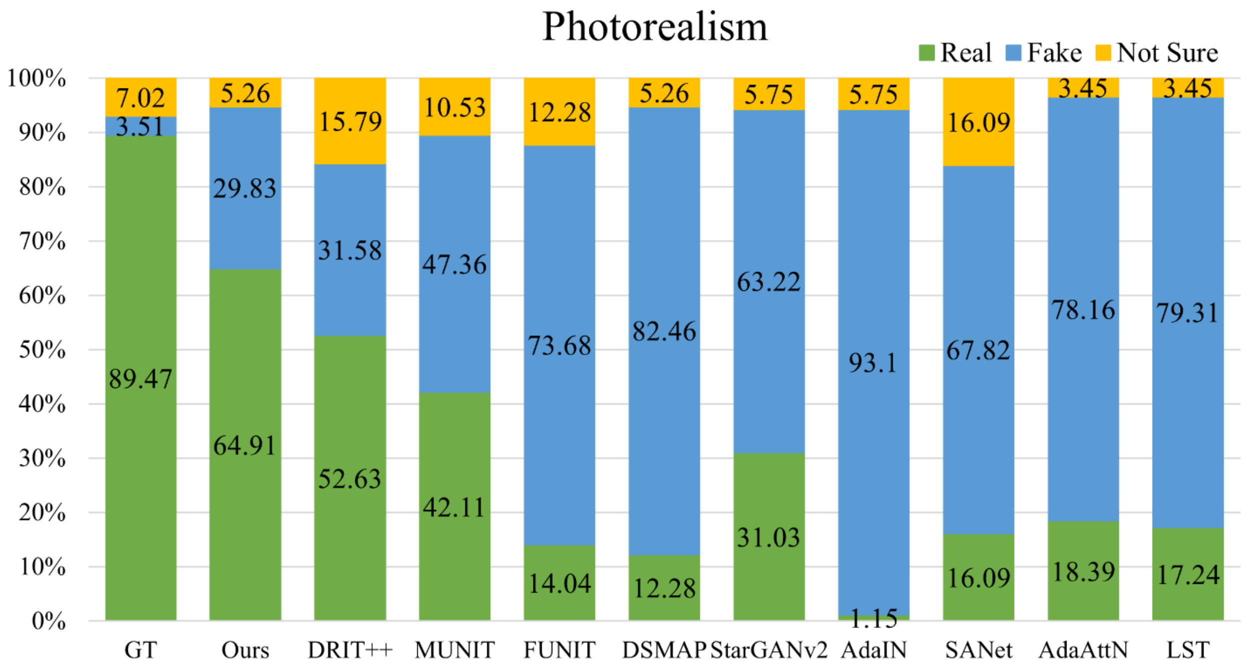
Ours (or Ours-opt): our translation models trained with segmented images.

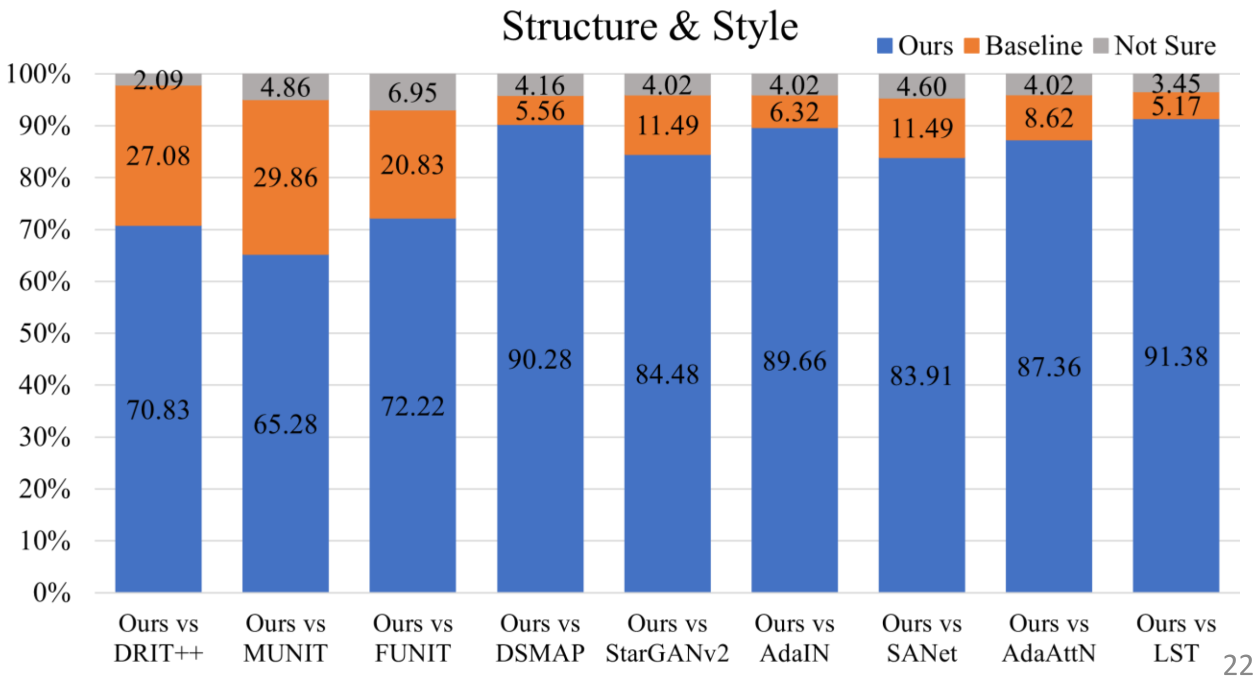
Input image from pikwizard,81dde04c1a0a2ac3f3682d680f2374bf. Style image from pexels,almudena-cathedral-madrid-423932.

*e-SSIM: SSIM on image edges

Experiments

	image-to-image translation					generic neural style transfer				
	DRIT++	MUNIT	FUNIT	DSMAP	StarGANv2	AdaIN	SANet	AdaAttN	LST	Ours
e-SSIM↑	0.5214	0.5653	0.4959	0.4790	0.4778	0.4962	0.4854	0.5194	0.4903	**0.6359**
Acc↑	0.8903	0.8678	0.77.14	0.9106	0.8788	0.7352	0.6193	0.6443	0.7071	**0.9486**
IS↑	2.6160	2.5916	2.5903	2.6580	2.6088	2.4082	2.1062	2.0928	1.7299	**2.7290**
IoU↑	0.6915	**0.7382**	0.5473	0.4975	0.4100	0.6642	0.7183	0.6532	0.6264	0.7257





Experiments

Comparison to image-to-image translation methods

Style references

Input

Input image from pikwizard, 074a69d48e93c913aa718a929aea3b96.
Style images from pexels.com,buildings-under-cloudy-sky-during-sunset-462331, by *Ed Lofdahl* and pexels,almudena-cathedral-madrid-423932.

Experiments

Comparison to image-to-image translation methods

Style references

MUNIT

Huang et al., "Multimodal unsupervised image-to-image translation," ECCV 2018.
Style images from pexels.com,buildings-under-cloudy-sky-during-sunset-462331, by *Ed Lofdahl* and pexels,almudena-cathedral-madrid-423932.

Experiments

Comparison to image-to-image translation methods

Style references

DSMAP

Chang et al., “Domain-specific mappings for generative adversarial style transfer,” ECCV 2020.
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Experiments

Comparison to neural style transfer methods

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AdaIN

Huang and Belongie, “Arbitrary style transfer in real-time with adaptive instance normalization,” ICCV 2017.
Style images from unsplash.com, 5omwAMDxmkU, unsplash.com, K4bvYKfXi3w, pexels.com, city-skyline-across-body-of-water-during-night-time-3586966/.

Experiments

Comparison to neural style transfer methods

Style references

AdaAttN

Liu et al., “AdaAttN: Revisit attention mechanism in arbitrary neural style transfer,” ICCV 2021.
Style images from unsplash.com, 5omwAMDxmkU, unsplash.com, K4bvYKfXi3w, pexels.com, city-skyline-across-body-of-water-during-night-time-3586966/.

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More Results

Input

Style reference

Input image from pexels.com, 4147341. Style image from unsplash.com, 5omwAMDxmkU.

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Style reference

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More Results

Input

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Input image from pexels.com, 4147341. Style image from pexels.com, city-skyline-across-body-of-water-during-night-time-3586966/.

Contribution

1) A new problem setting for style transfer: **photorealistic style transfer for architectural photographs** of different times of day.
2) An image-to-image translation neural network with disentanglement representation that separately **considers style transfer for image foreground and background respectively**, accompanied with simple but effective **geometry losses** designed for image content preservation.
3) A **new dataset of architectural photographs** and an extensive benchmark for architectural style transfer.

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Project page

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