Reflection Separation using a Pair of Unpolarized and Polarized Images

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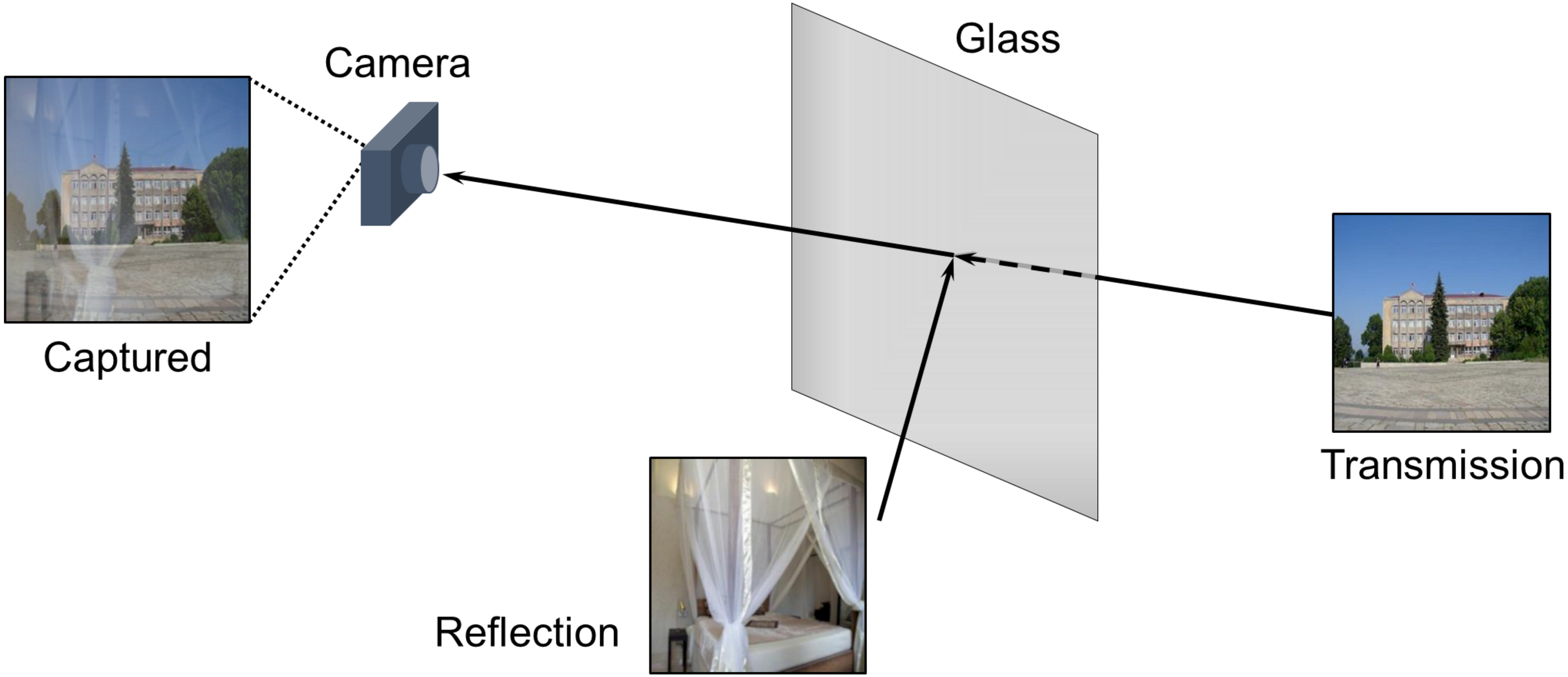
Reflection Separation



Reflection Separation

- An ill-posed problem

Captured
I

Reflection
I_r

Transmission
I_t

Previous Solutions

Additional Priors

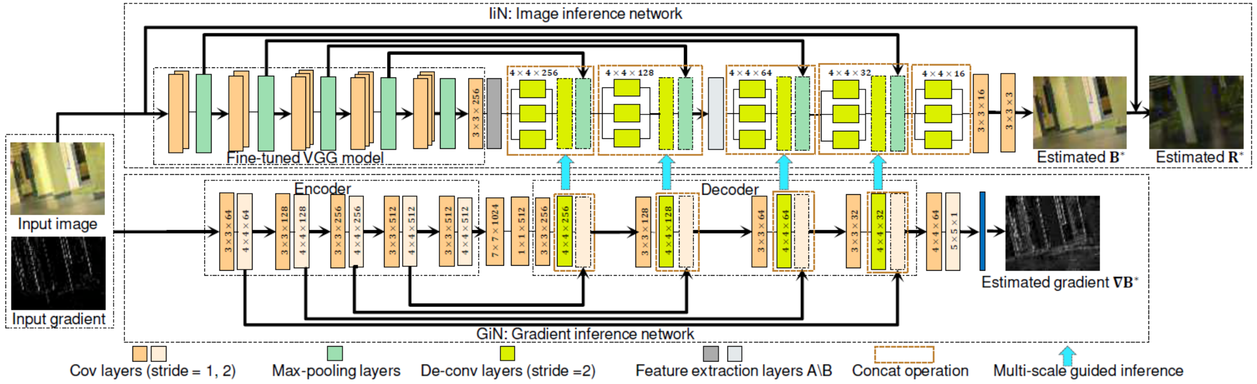
- Gradient sparsity priors
  [Levin et al. 07] [Wan et al. 18]

- Relative smoothness priors
  [Li et al. 14] [Arvanitopoulos et al. 17]

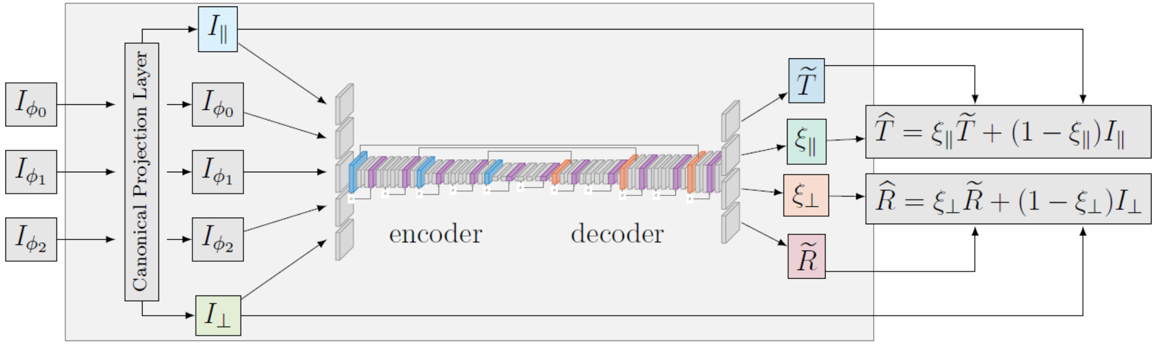
Additional Input

- Different viewpoints
  [Gai et al. 12] [Guo et al. 14] [Xue et al. 15]

- Different polarization angles
  [Schechner et al. 00] [Wieschollek et al. 18]



[Wan et al. 18]



[Wieschollek et al. 18]

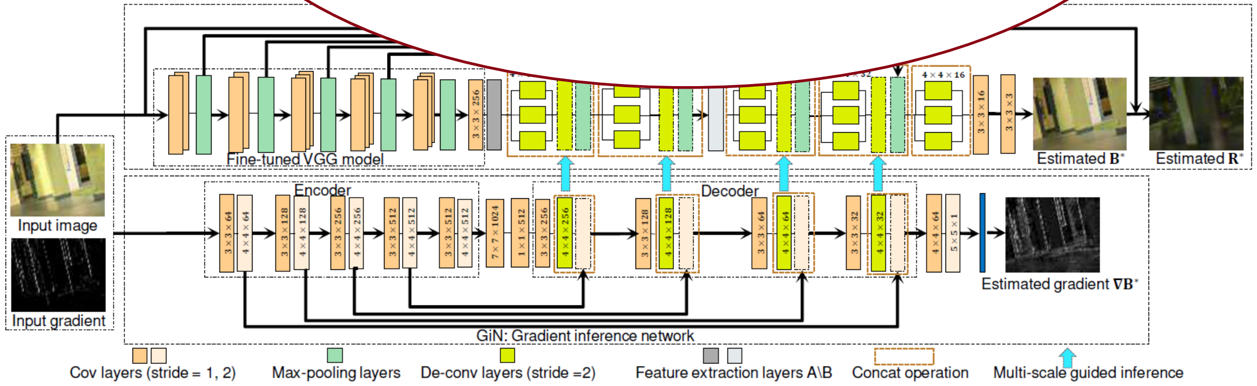
Previous Solutions

Additional Priors

- Gradient sparsity priors

[Levin et al. 07] [Wan et al. 18]

Violate in real-world scenarios



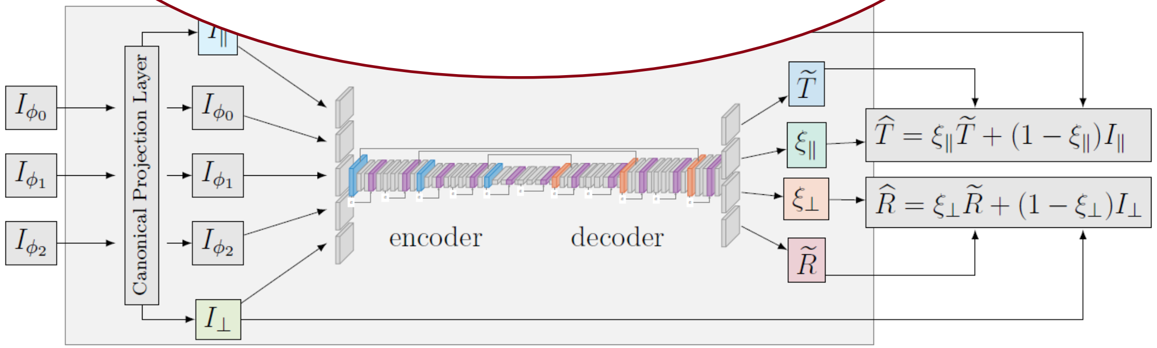
[Wan et al. 18]

Additional Input

- Different viewpoints

[Gai et al. ... l. 14] [Xue et al. 15]

Complicated capturing operations



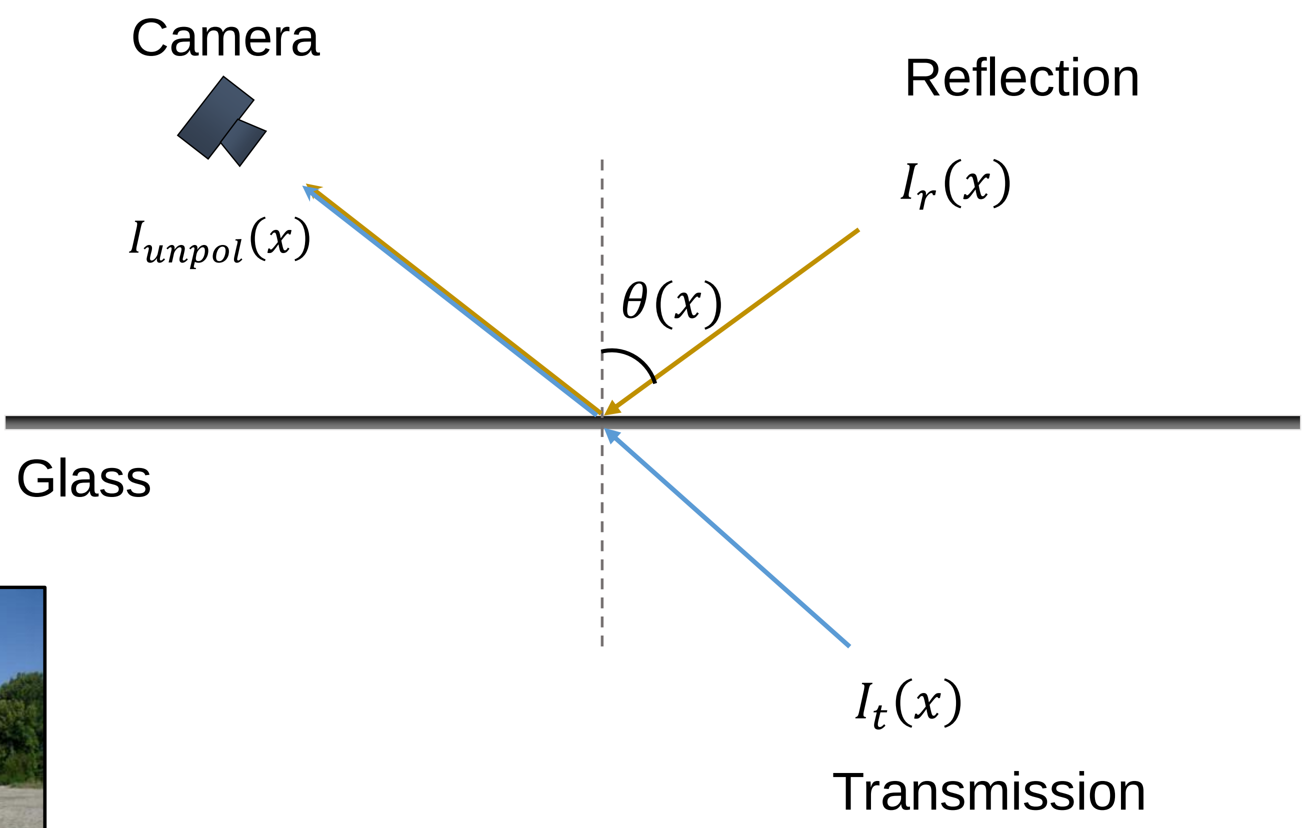
[Wieschollek et al. 18]

We design an end-to-end neural network which takes a pair of (un)polarized images for reflection separation based on a new physical image formation model.

New Setup: (un)polarized images

Without polarizer
in front of the camera

$$I_{unpol}(x) = I_r(x) \cdot \frac{\xi(x)}{2} + I_t(x) \cdot \frac{2 - \xi(x)}{2}$$



I_{unpol}

I_r

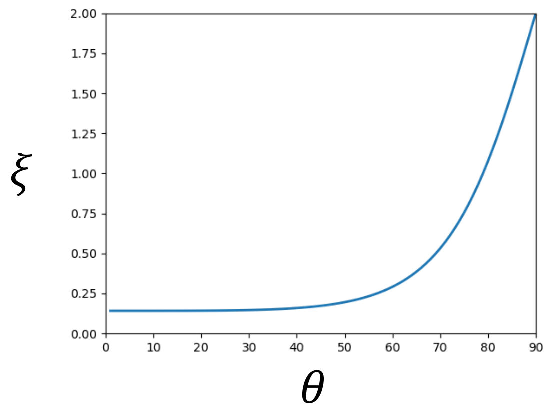
I_t

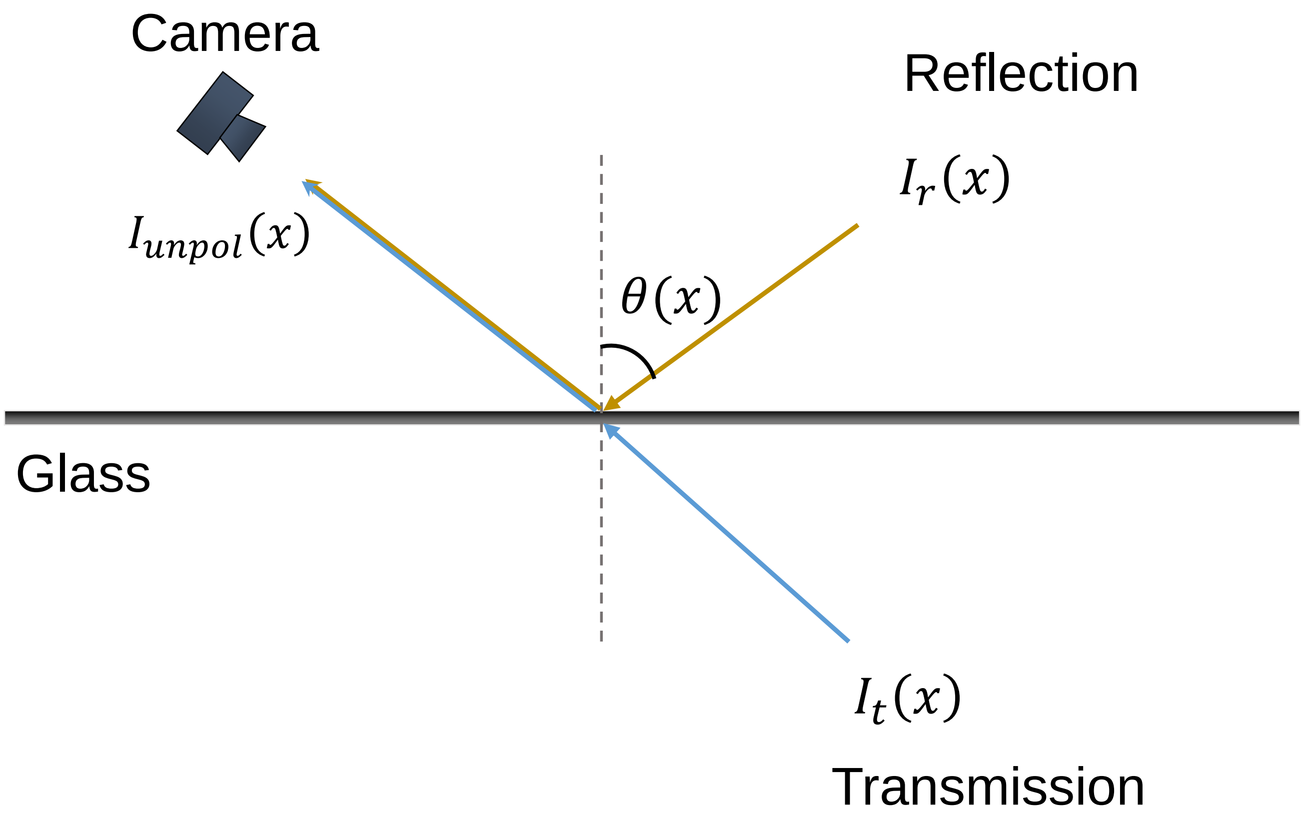
New Setup: (un)polarized images

Without polarizer
in front of the camera

$$I_{unpol}(x) = I_r(x) \cdot \frac{\xi(x)}{2} + I_t(x) \cdot \frac{2 - \xi(x)}{2}$$

$$\xi(x) = f_1(\theta(x))$$



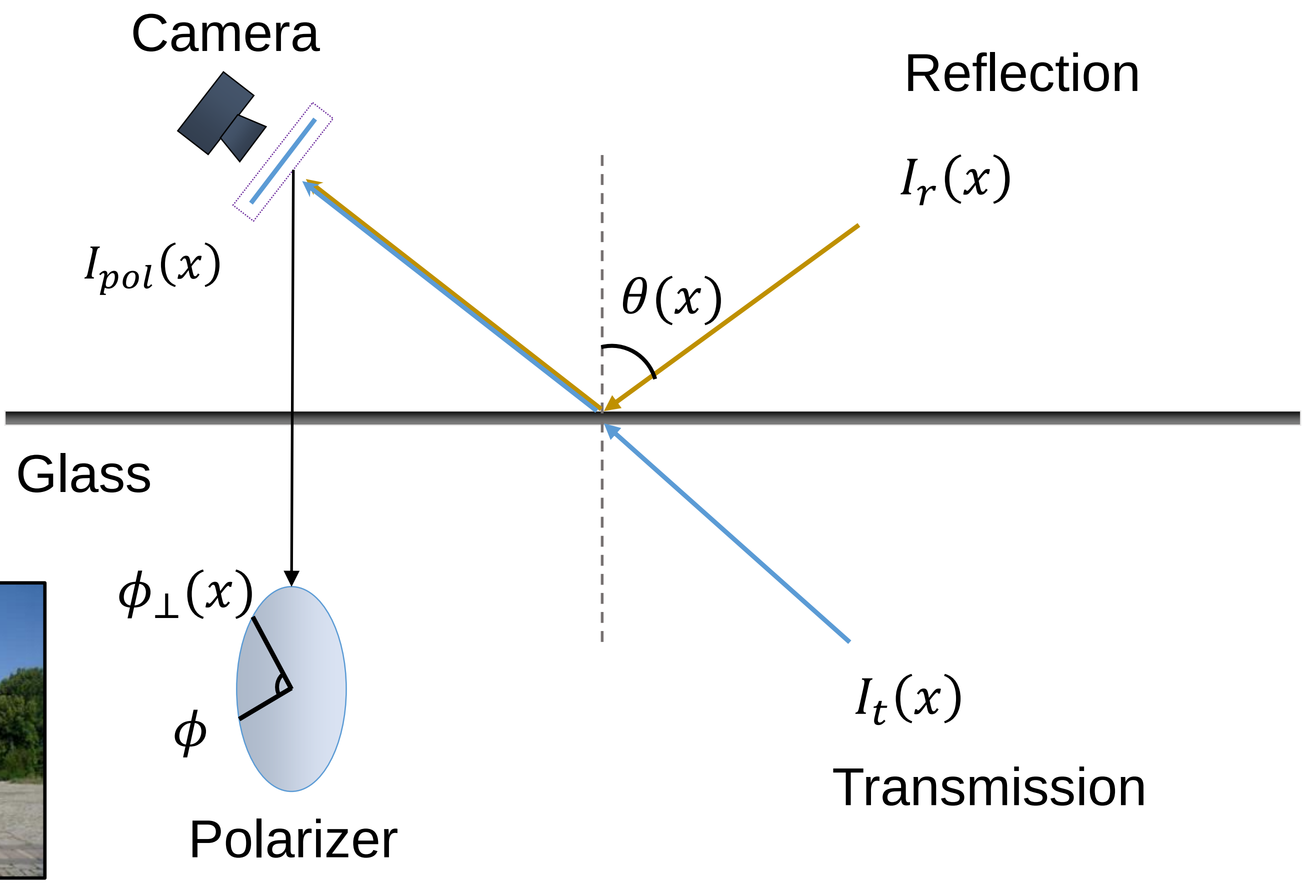


$\theta(x)$ is the angle of incidence.

New Setup: (un)polarized images

With polarizer
in front of the camera

$$I_{pol}(x) = I_r(x) \cdot \frac{\zeta(x)}{2} + I_t(x) \cdot \frac{1-\zeta(x)}{2}$$




I_{pol}


I_r

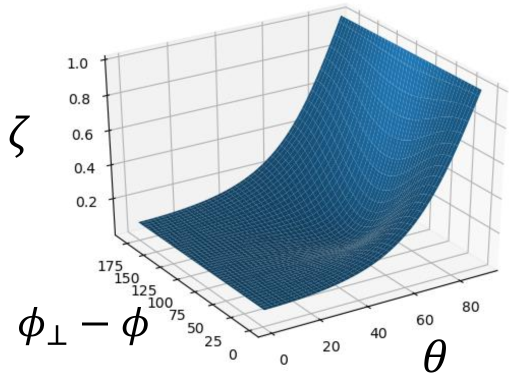

I_t

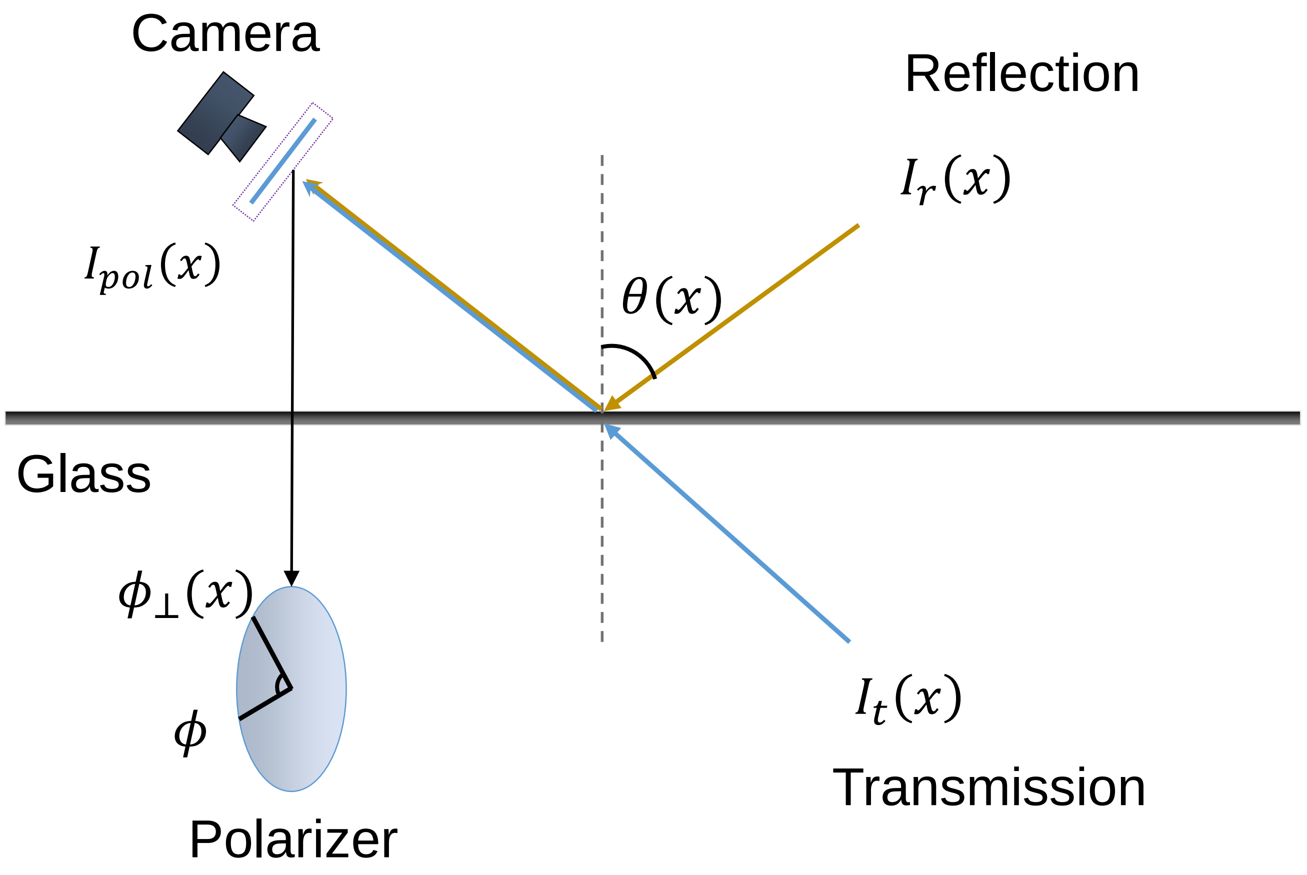
New Setup: (un)polarized images

With polarizer
in front of the camera

$$I_{pol}(x) = I_r(x) \cdot \frac{\zeta(x)}{2} + I_t(x) \cdot \frac{1-\zeta(x)}{2}$$

$$\zeta(x) = f_2(\theta(x), \phi_\perp(x))$$





$\phi_\perp(x)$ is the orientation of the polarizer for the best transmission of the component perpendicular to the plane of incidence (PoI).

New Setup: (un)polarized images

Without polarizer:

$$I_{unpol}(x) = I_r(x) \cdot \frac{\xi(x)}{2} + I_t(x) \cdot \frac{2 - \xi(x)}{2}$$

With polarizer:

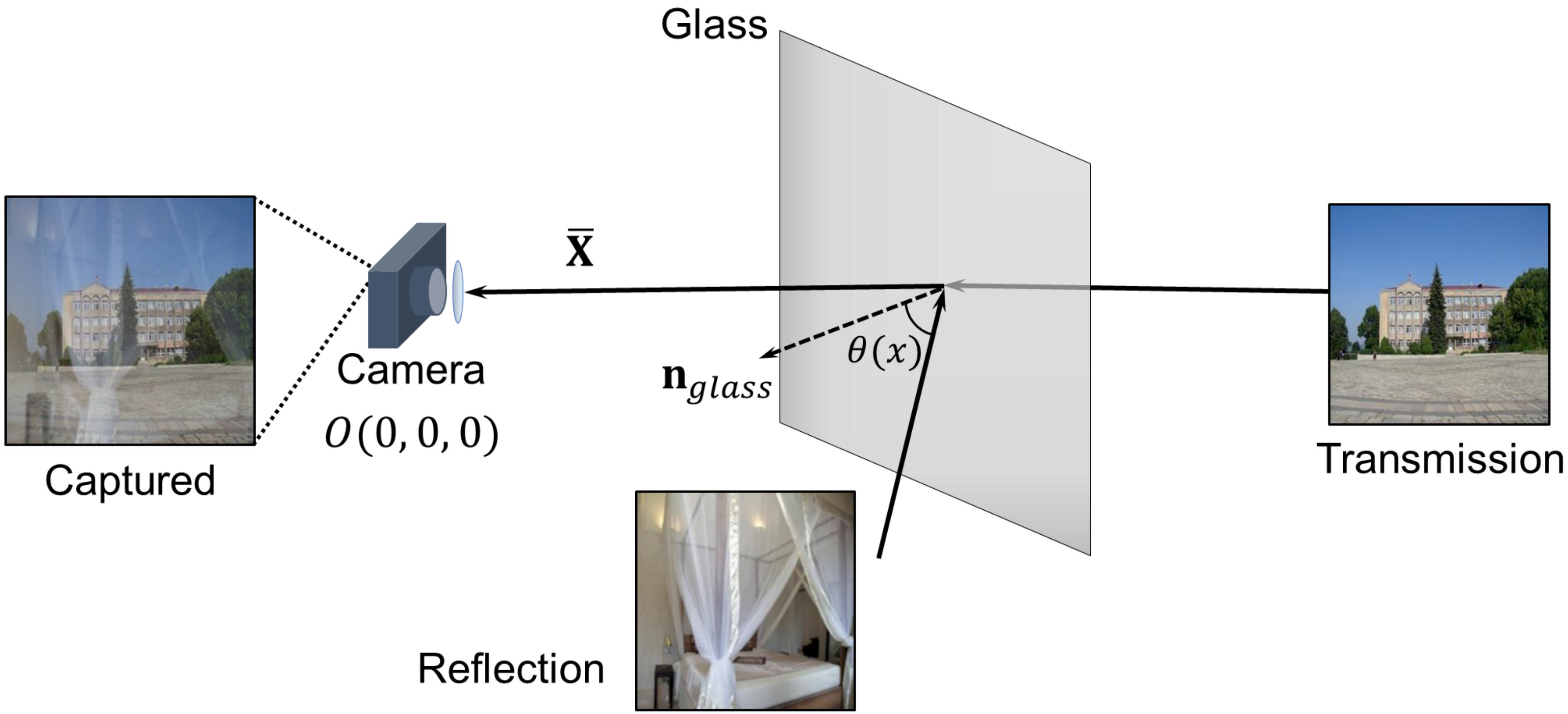
$$I_{pol}(x) = I_r(x) \cdot \frac{\zeta(x)}{2} + I_t(x) \cdot \frac{1 - \zeta(x)}{2}$$

$$\left.\begin{array}{l} I_{unpol}(x), I_{pol}(x) \\ \theta(x), \phi_{\perp}(x) \end{array}\right] \Rightarrow I_t(x),\ I_r(x)$$

How to compute $\theta(x)$ and $\phi_{\perp}(x)$?

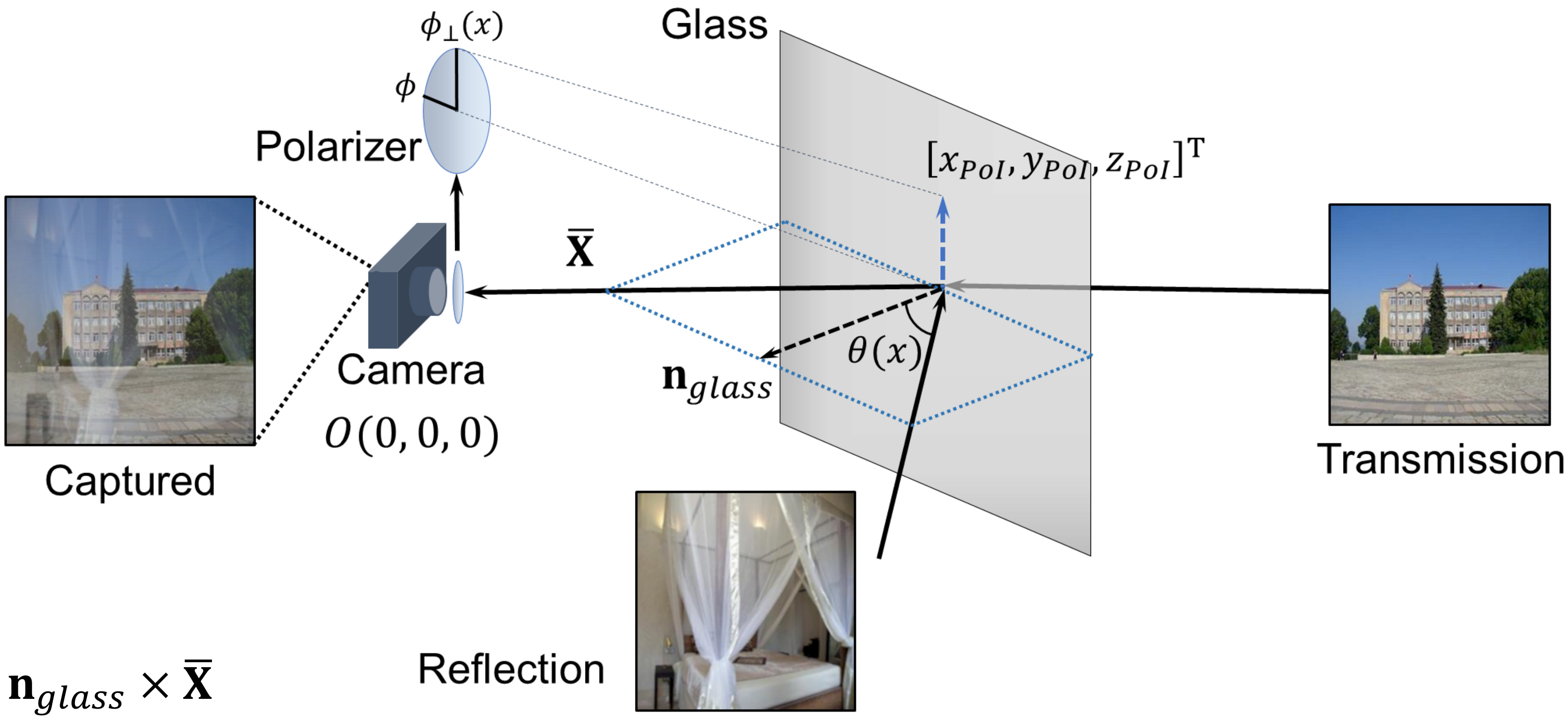
Physical Image Formation Model

$$\theta(x) = \arccos(|\mathbf{n}_{glass} \cdot \bar{\mathbf{X}}|)$$



Physical Image Formation Model

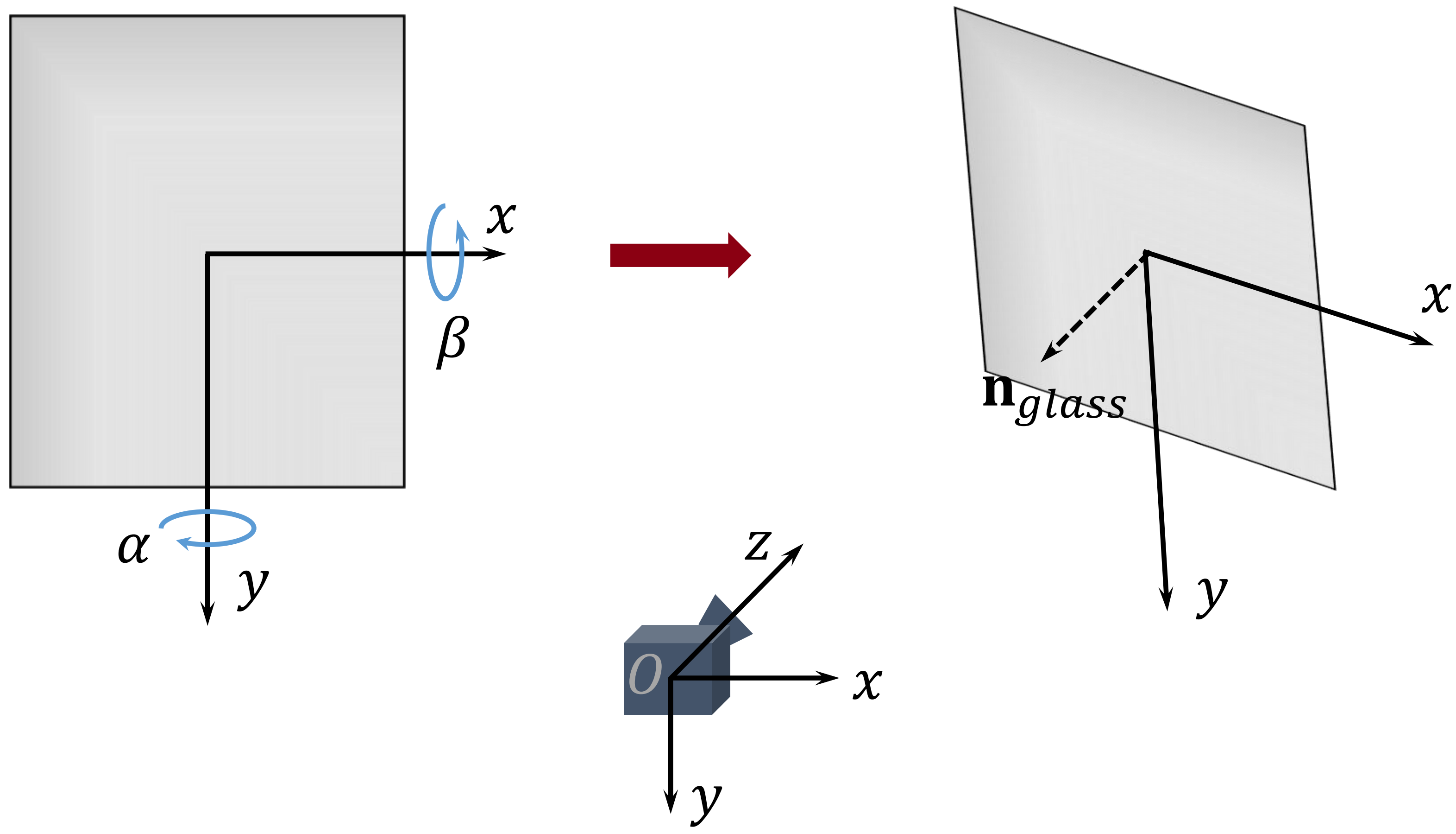
$$\theta(x) = \mathrm{arcos}(|\mathbf{n}_{glass} \cdot \bar{\mathbf{X}}|)$$



$$\phi_{\perp}(x) = \arctan \frac{y_{PoI}}{x_{PoI}}$$

where $[x_{PoI}, y_{PoI}, z_{PoI}]^{\mathrm{T}} = \mathbf{n}_{glass} \times \bar{\mathbf{X}}$

Physical Image Formation Model



$$\alpha, \beta \Rightarrow \mathbf{n}_{glass}$$

Physical Image Formation Model

Without polarizer:

$$I_{unpol}(x) = I_r(x) \cdot \frac{\xi(x)}{2} + I_t(x) \cdot \frac{2 - \xi(x)}{2}$$

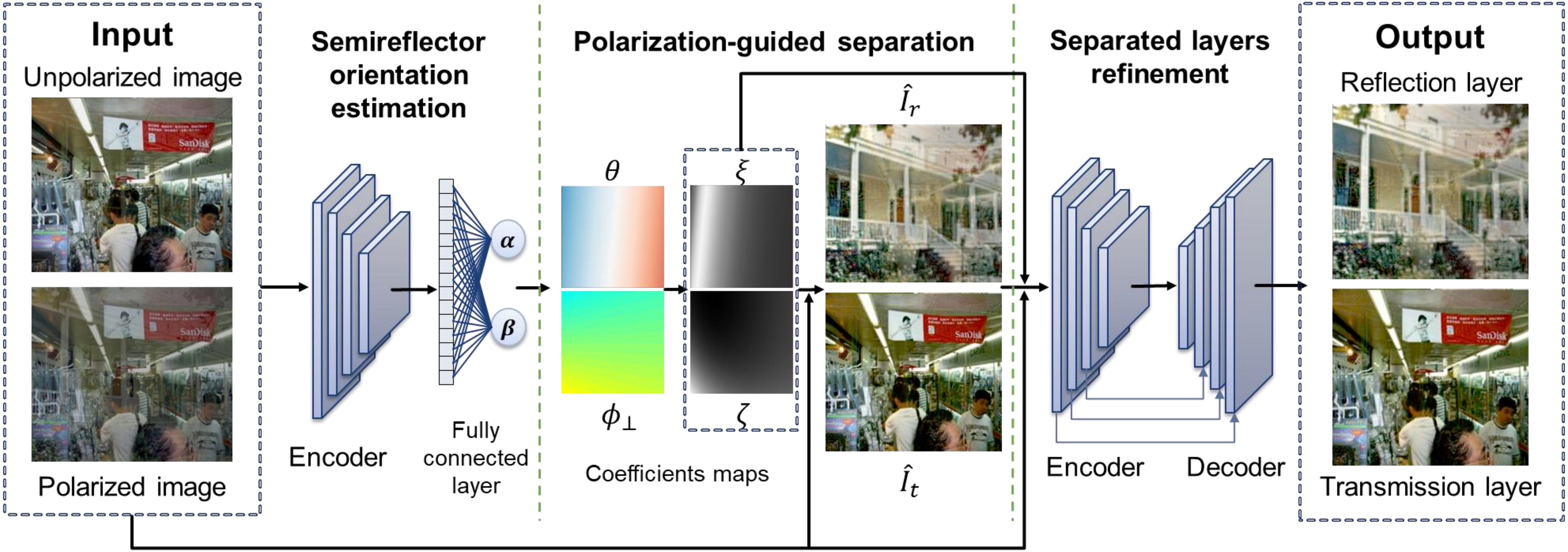
With polarizer:

$$I_{pol}(x) = I_r(x) \cdot \frac{\zeta(x)}{2} + I_t(x) \cdot \frac{1 - \zeta(x)}{2}$$

$$\left.\begin{aligned} &I_{unpol}(x), I_{pol}(x) \\ &\theta(x), \phi_{\perp}(x) \end{aligned}\right] \Rightarrow I_t(x),\ I_r(x)$$

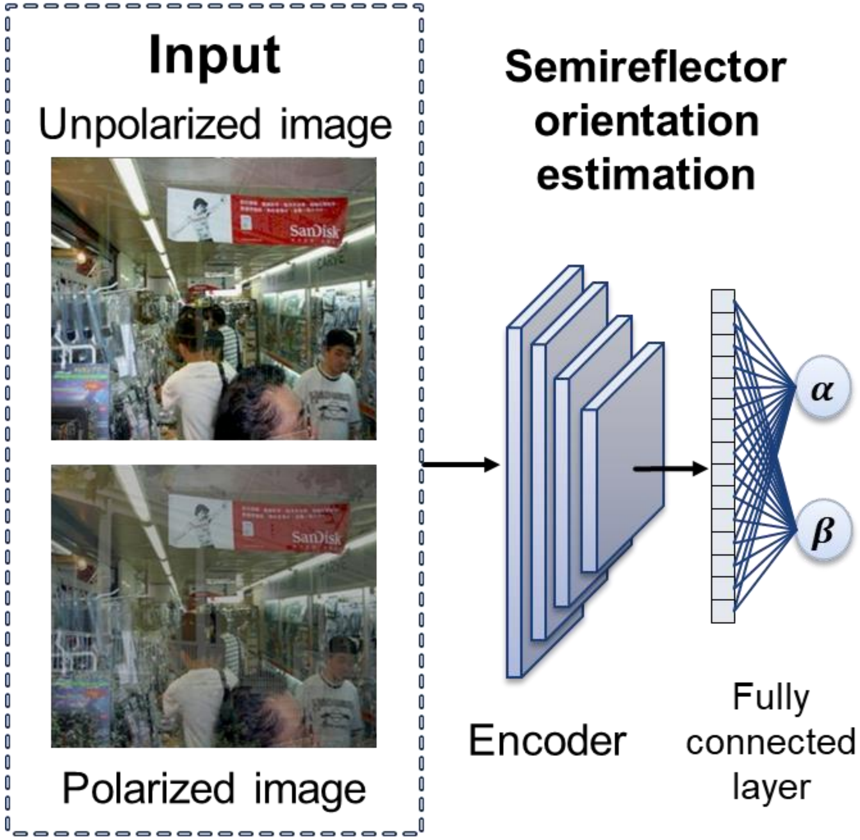
$$\left.\begin{aligned} &I_{unpol}(x), I_{pol}(x) \\ &\alpha, \beta \end{aligned}\right] \Rightarrow I_t(x),\ I_r(x)$$

Reflection Separation Network



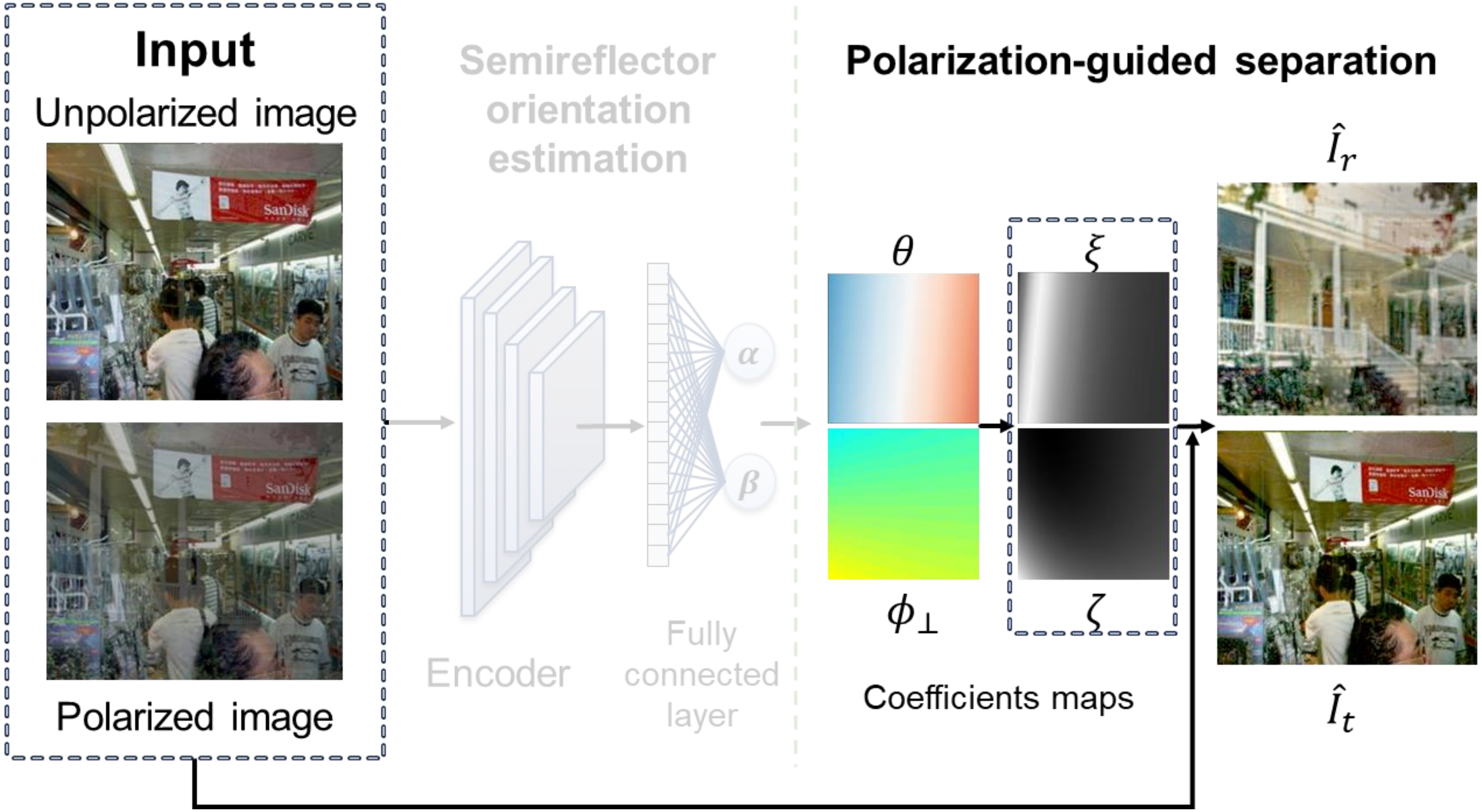
Reflection Separation Network

- Semireflector orientation estimation module



Reflection Separation Network

- Polarization-guided separation module



$$\theta(x) = \arccos\left(\left|\mathbf{n}_{glass} \cdot \overline{\mathbf{X}}\right|\right)$$

$$\phi_\perp(x) = \arctan \frac{y_{PoI}}{x_{PoI}}$$

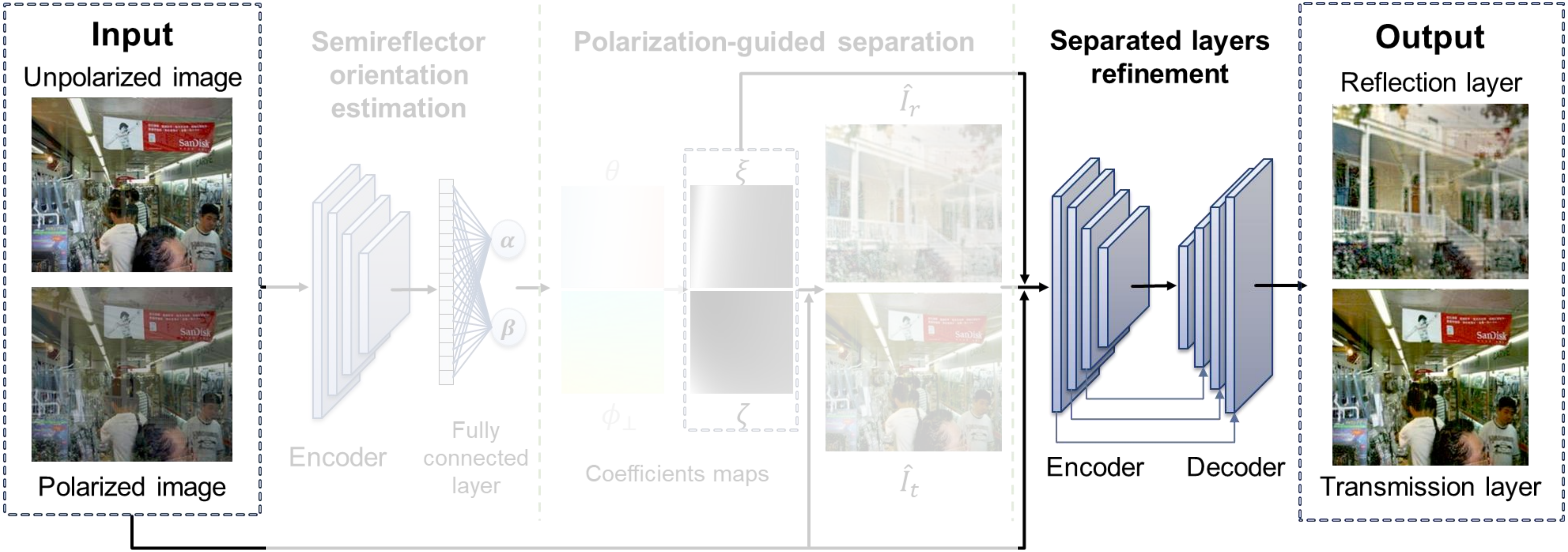
$$[x_{PoI}, y_{PoI}, z_{PoI}]^{\mathrm{T}} = \mathbf{n}_{glass} \times \overline{\mathbf{X}}$$

$$\left.\begin{array}{l} I_{unpol}(x), I_{pol}(x) \\ \theta(x), \phi_\perp(x) \end{array}\right] \Rightarrow \hat{I}_t(x), \hat{I}_r(x)$$

Reflection Separation Network

- Separated layers refinement module

$$\hat{I}_t(x), \hat{I}_r(x) \Rightarrow I_t(x), I_r(x)$$

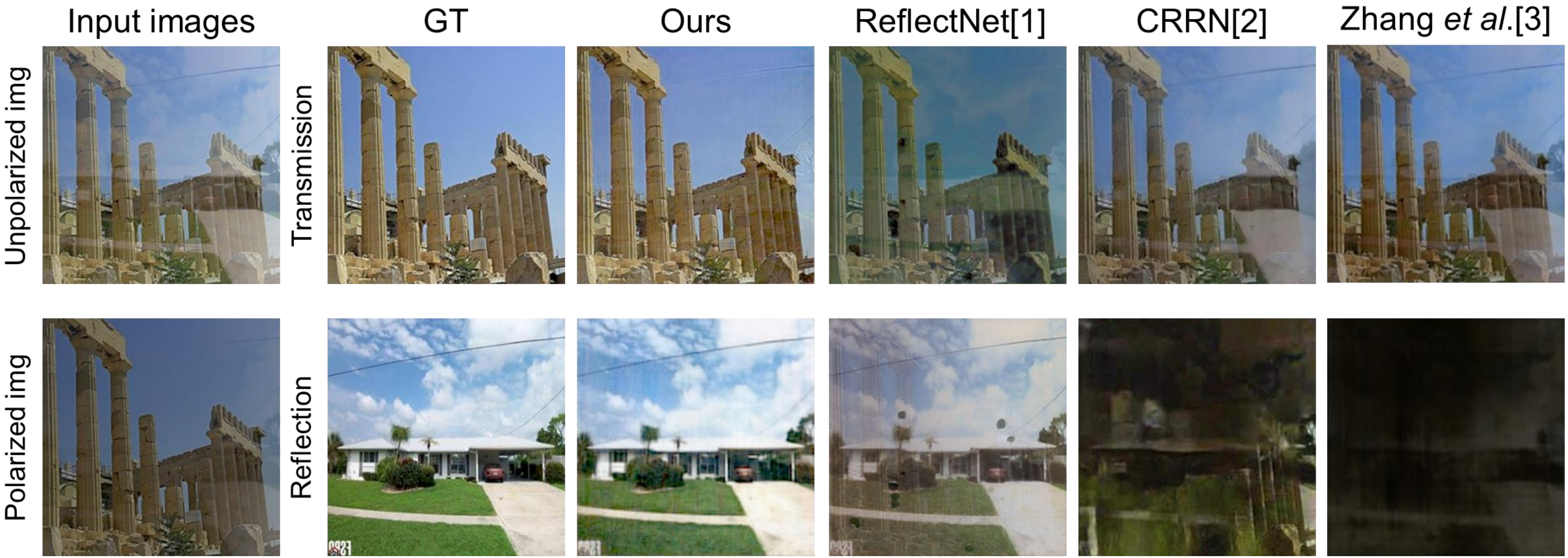


Evaluation on Synthetic Data

		Ours	Ours-Initial	ReflectNet[1]-Finetuned	Ours-2% noise	Ours-8% noise	Ours-16% noise
Transmission	SSIM	**0.9708**	0.8324	0.9627	0.9691	0.9668	0.9619
	PSNR	**28.23**	21.61	27.52	28.08	27.31	27.17
Reflection	SSIM	**0.8953**	0.6253	0.8303	0.8785	0.8418	0.8022
	PSNR	**20.92**	13.90	18.50	20.53	19.18	18.26

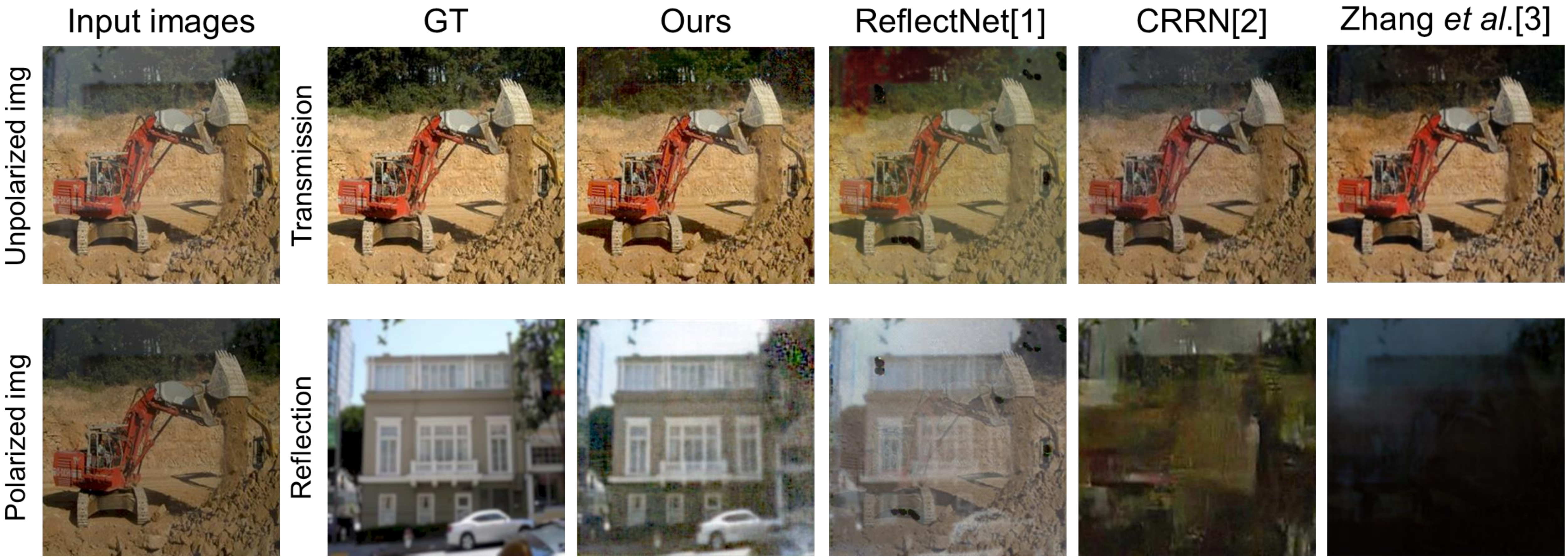
[1] P. Wieschollek, O. Gallo, J. Gu, and J. Kautz. Separating reflection and transmission images in the wild. In Proc. ECCV, 2018.

Evaluation on Synthetic Data



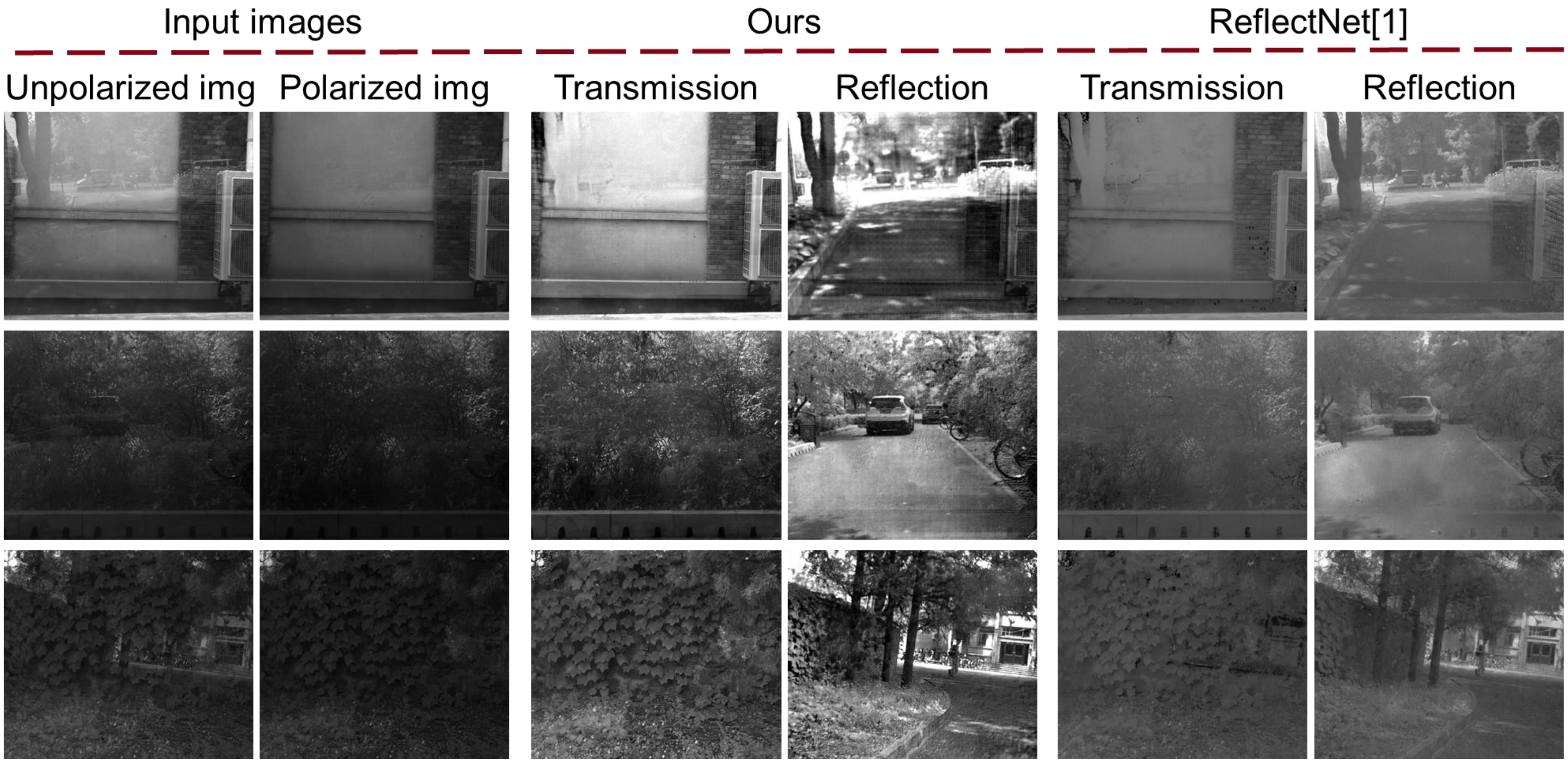
[1] P. Wieschollek, O. Gallo, J. Gu, and J. Kautz. Separating reflection and transmission images in the wild. ECCV, 2018.
[2] R. Wan, B. Shi, L.-Y. Duan, A.-H. Tan, and A. C. Kot. CRRN: Multi-scale guided concurrent reflection removal network. CVPR, 2018
[3] X. Zhang, R. Ng, and Q. Chen. Single image reflection separation with perceptual losses. CVPR, 2018.

Evaluation on Synthetic Data



[1] P. Wieschollek, O. Gallo, J. Gu, and J. Kautz. Separating reflection and transmission images in the wild. In Proc. ECCV, 2018.
[2] R. Wan, B. Shi, L.-Y. Duan, A.-H. Tan, and A. C. Kot. Crrn: Multi-scale guided concurrent reflection removal network. In Proc. CVPR, 2018
[3] X. Zhang, R. Ng, and Q. Chen. Single image reflection separation with perceptual losses. In Proc. CVPR, 2018.

Evaluation on Real-World Data



[1] P. Wieschollek, O. Gallo, J. Gu, and J. Kautz. Separating reflection and transmission images in the wild. In Proc. ECCV, 2018.

Conclusion

- A simple while effective setup for reflection separation using a pair of (un)polarized images
- A well-posed physical image formation model
- An end-to-end deep neural network designed according to the physical model

Thank you!

Poster #83

Thursday, December 12th, 05:00 - 07:00 PM