Polarimetric 3D Reconstruction and Image Separation

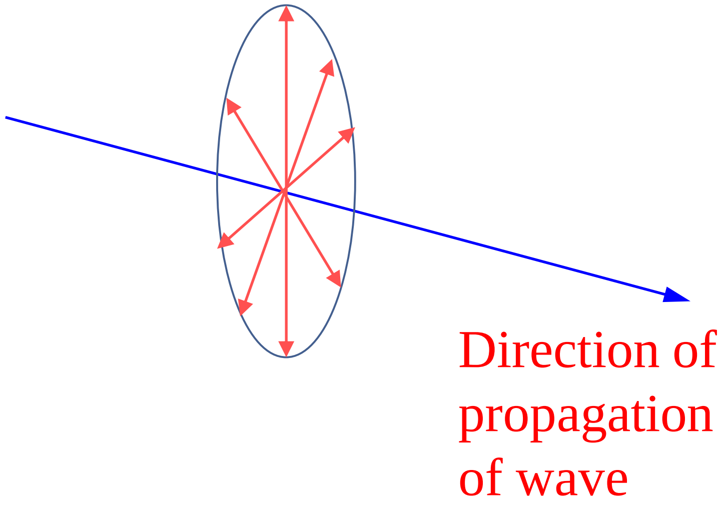
Zhaopeng Cui
ETH Zurich
12.19.2019

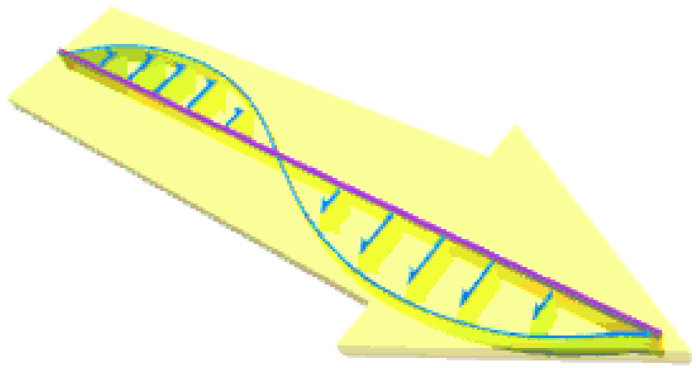
Outline

- Polarization and Polarizer
- Polarimetric 3D Reconstruction
  - Polarimetric Multiple-View Stereo [CVPR’2017]
  - Poalrimetric Dense Monocular SLAM [CVPR’2018]
  - Poalrimetric Relative Pose Estimation [ICCV’2019]
- Polarimetric Reflection Separation [NeurIPS’2019]
- Conclusion

Polarization

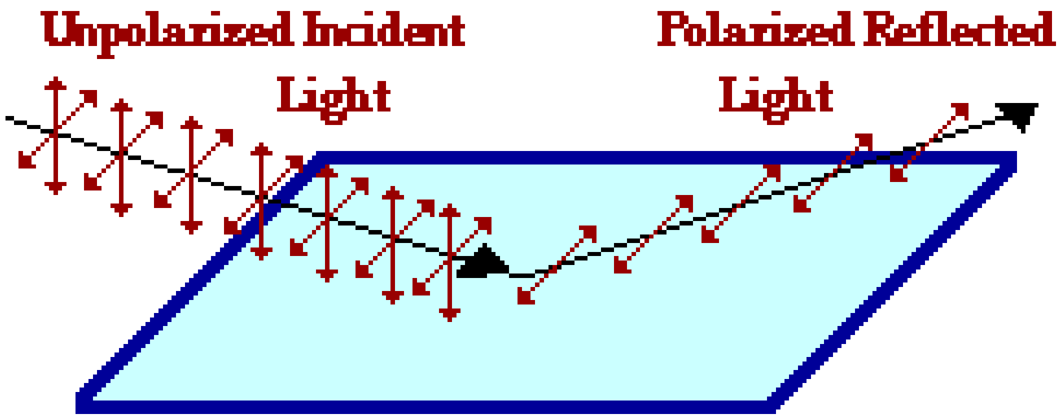
- Polarization is a characteristic of all transverse waves.
- Oscillation which take places in a transverse wave in many different directions is said to be unpolarized.
- In an unpolarized transverse wave oscillations may take place in any direction at right angles to the direction in which the wave travels.





Polarization by Reflection

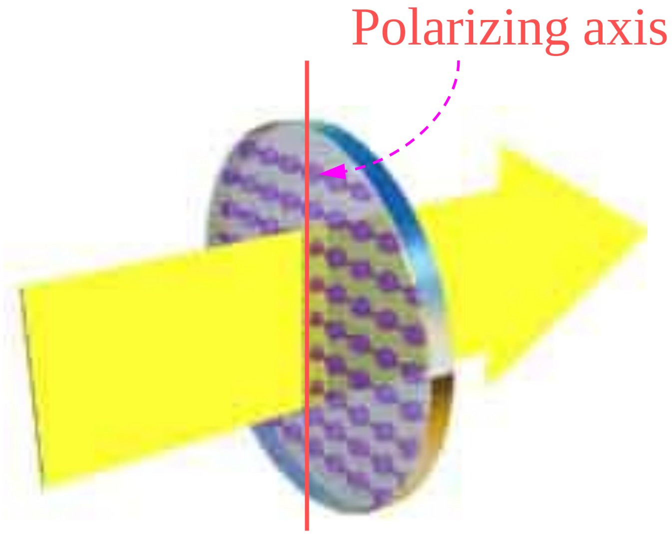
- Unpolarized light can be polarized, either partially or completely, by reflection.
- The amount of polarization in the reflected beam depends on the angle of incidence.

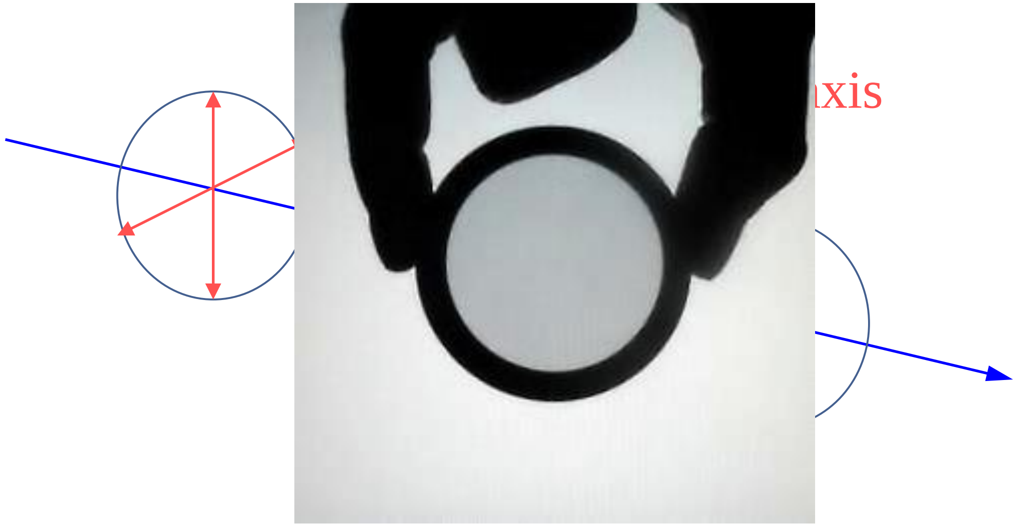


Reflection of light off of non-metallic surfaces results in some degree of polarization parallel to the surface.

Polarizer

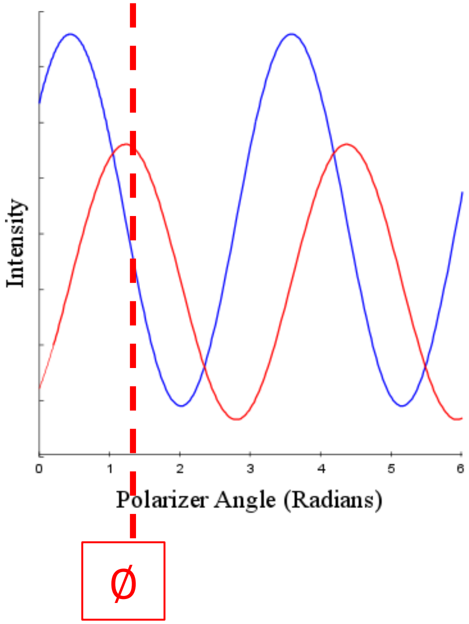
- Polarizer is made from long chain molecules oriented with their axis perpendicular to the polarizing axis;
- These molecules preferentially absorb light that is polarized along their length.

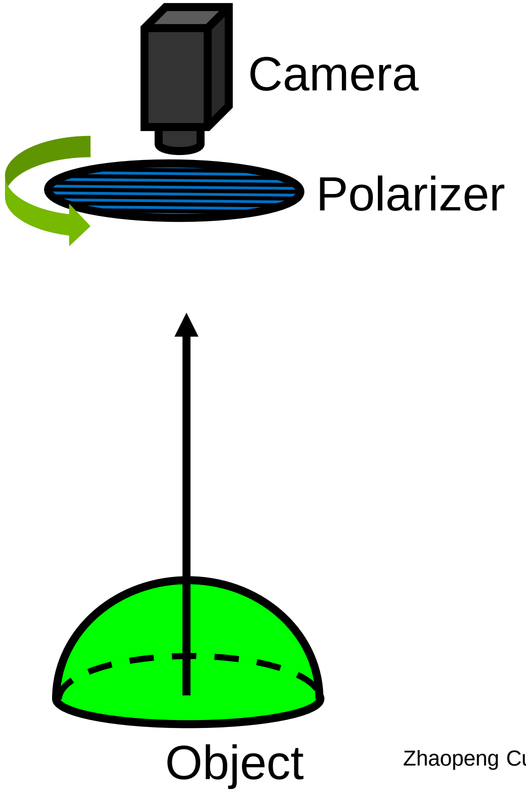




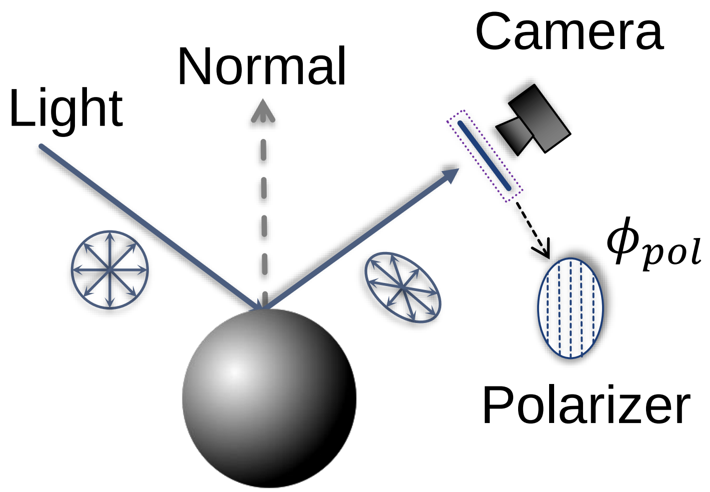
Polarimetric Imaging

- Images with a Rotating Polarizer
  - Pixel intensity varies with polarizer angles
  - We can recover geometric information from polarized images





Surface Normal from Polarization



- Estimation of the azimuth angle φ (diffuse reflection):

$$I(\phi_{pol}) = \frac{I_{max} + I_{min}}{2} + \frac{I_{max} - I_{min}}{2} \cos(2(\phi_{pol} - \phi))$$

$\varphi = \phi$ or $\varphi = \phi + \pi$

- Estimation of the zenith angle θ (diffuse reflection):

$$\rho = \frac{I_{max} - I_{min}}{I_{max} + I_{min}} = \frac{(n - 1/n)^2 \sin^2\theta}{2 + 2n^2 - (n + 1/n)\sin^2\theta + 4\cos\theta\sqrt{n^2 - \sin^2\theta}}$$

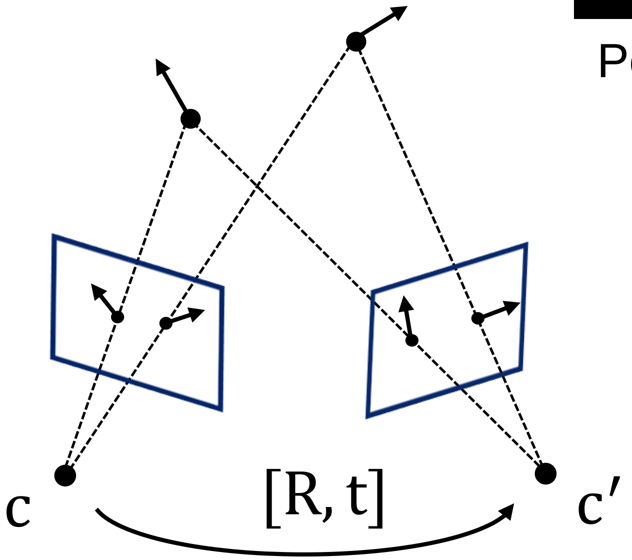
- Estimation of the surface normal v:

$$\mathrm{v} = (v_x, v_y, v_z)^{\mathrm{T}} = (\cos\varphi\sin\theta, -\sin\varphi\sin\theta, -\cos\theta)^{\mathrm{T}}$$

Polarimetric 3D Reconstruction

Polarimetric Multiple-View Stereo

Polarimetric Dense Monocular SLAM



Polarimetric Relative Pose Estimation

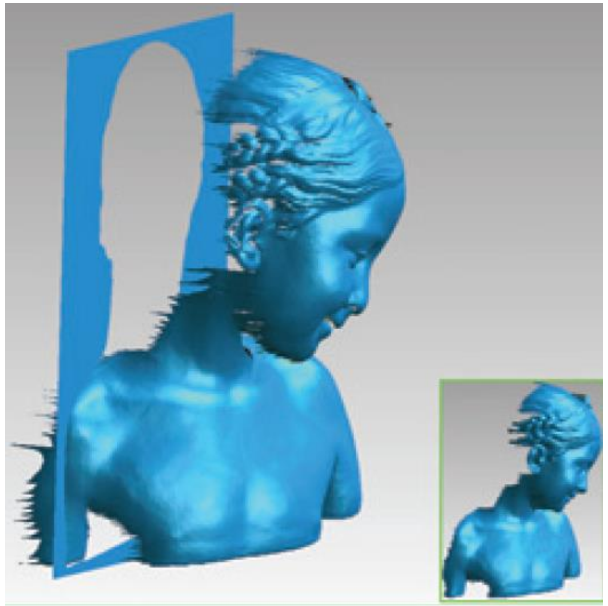
Traditional Multi-View Stereo

- Given several images of the same object or scene, compute a representation of its 3D shape.
- Traditional methods usually failed for *featureless* objects.

Input Sample

Traditional MVS Results

Shape from Surface Normal



[Xie et al. CVPR’19]

Challenges

Surface normal estimation from polarization is hard:

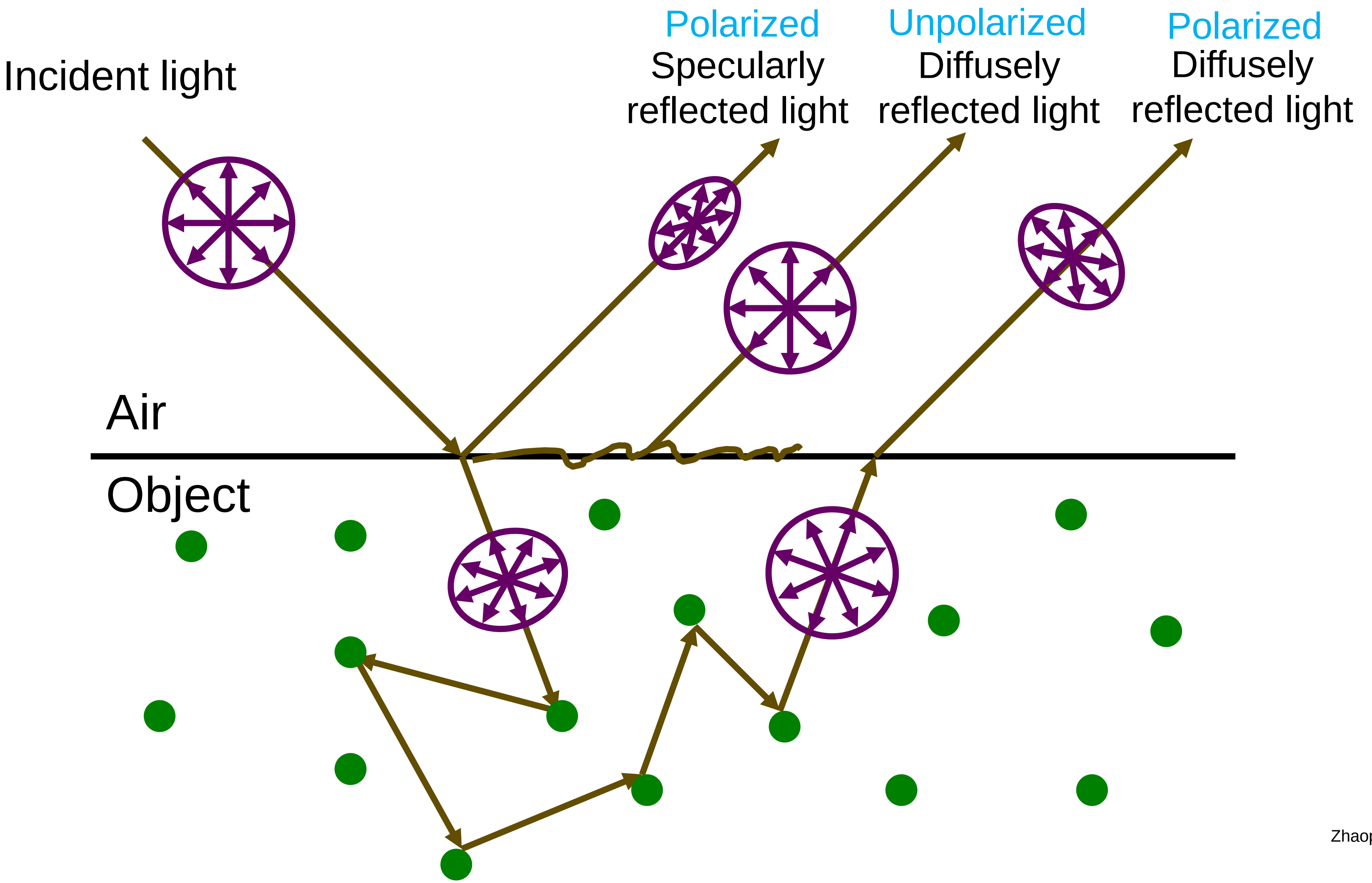
- Refractive distortion: Zenith angle estimation requires the knowledge of the refractive index.
- Azimuthal ambiguity: The estimation of the azimuthal angle has π-ambiuity.

$$I(\phi_{pol}) = \frac{I_{max} + I_{min}}{2} + \frac{I_{max} - I_{min}}{2} \cos(2(\phi_{pol} - \phi))$$

$\varphi = \phi$ or $\varphi = \phi + \pi$

- Mixed reflection in real environment.

Mixed Reflection



Polarimetric Multiple View Stereo [CVPR'17]

Proposition 1. *Under unpolarized illumination, the measured scene radiance from a reflective surface through a linear polarizer at a polarization angle* ψ_{pol} *is*

$$I(\emptyset_{pol}) = \frac{I_{max} + I_{min}}{2} + \frac{I_{max} - I_{min}}{2} \cos\left(2(\emptyset_{pol} - \emptyset)\right),$$

$where\, I_{max}\ and\, I_{min}\ are$ *the maximum and minimum measured radiance.*

The phase angle $\emptyset$ *is related to the azimuth angle* φ *as follows:*

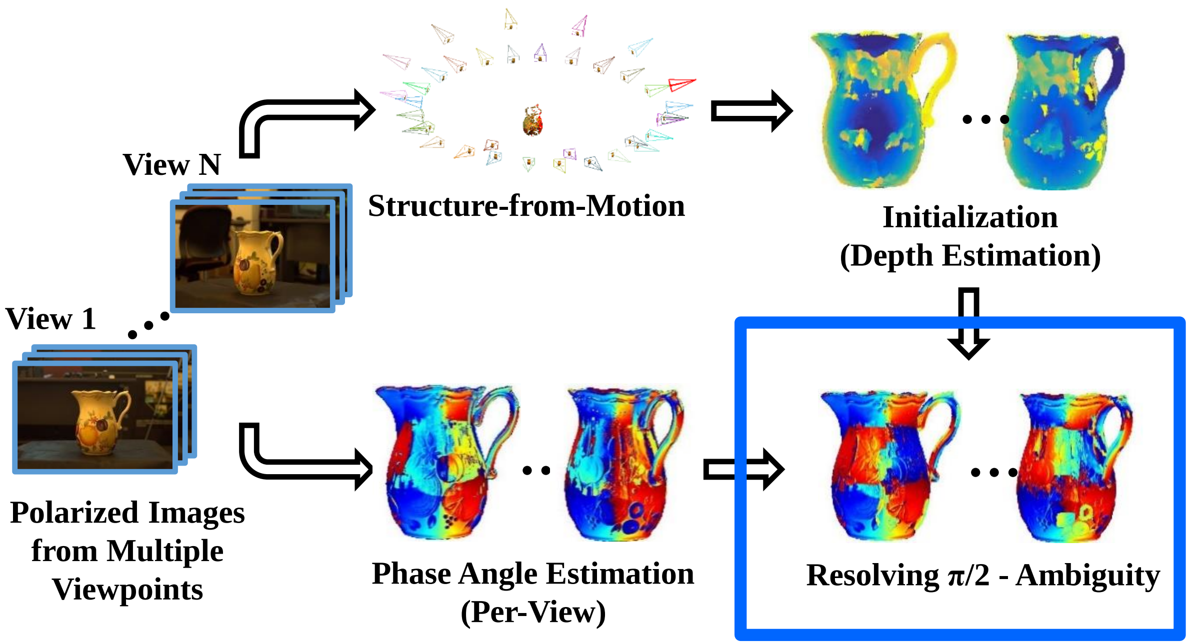
$$\emptyset = \begin{cases} \varphi & if\ polarized\ diffuse\ reflection\ dominates \\ \varphi - \frac{\pi}{2} & otherwise \end{cases}$$

$\pi/2$-ambiguity

* *The azimuthal (π) ambiguity still holds.*

Polarimetric Multiple View Stereo [CVPR’17]

- Exploit polarimetric information for dense reconstruction:
  - Use geometric information to help resolve ambiguities of polarimetric information

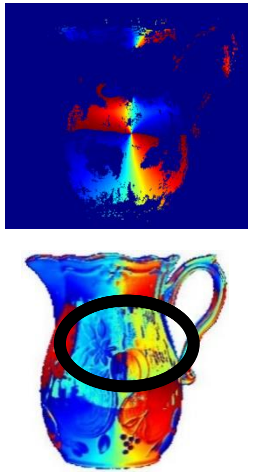


Polarimetric Multiple View Stereo [CVPR'17]

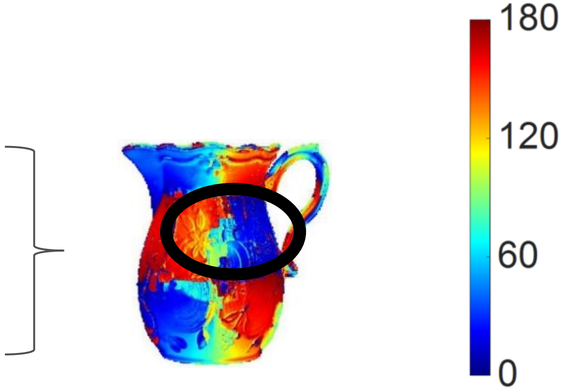
- Use geometric information to help resolve $\pi/2$-ambiguity

Initial depth

Depth after consistency check



Phase angle map



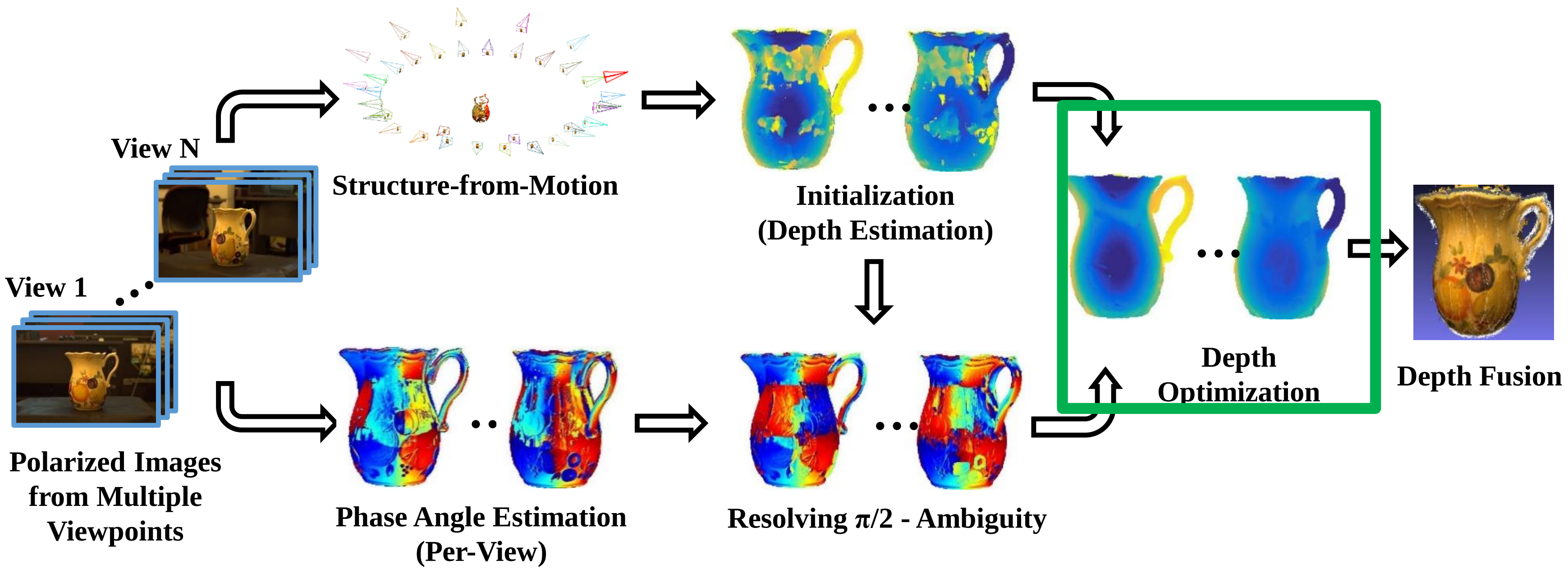
Azimuth angle map (after solving $\pi/2$-ambiguity)

$$E(\{f_p\}) = \sum_{p\in\mathcal{P}} D(f_p) + \lambda \sum_{p,q\in\mathcal{N}} S(f_p, f_q) \qquad f_p = \begin{cases} 0, & diffused\ dominates \\ 1, & specular\ dominates \end{cases}$$

$D(f_p)$ enforces consistency with MVS at well-textured regions.
$S(f_p, f_q)$ enforces neighboring pixels to have similar azimuth angles.

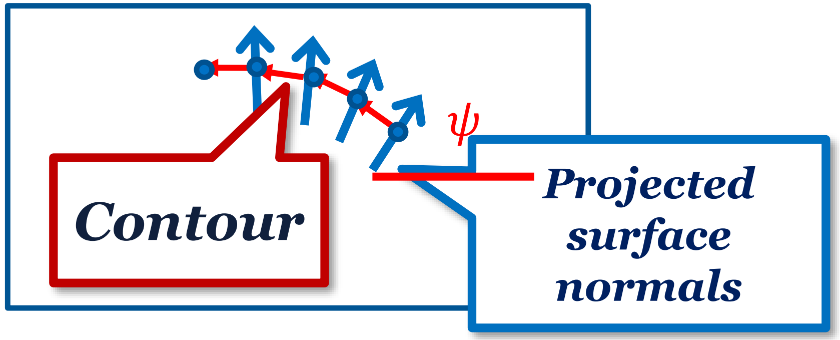
Polarimetric Multiple View Stereo [CVPR'17]

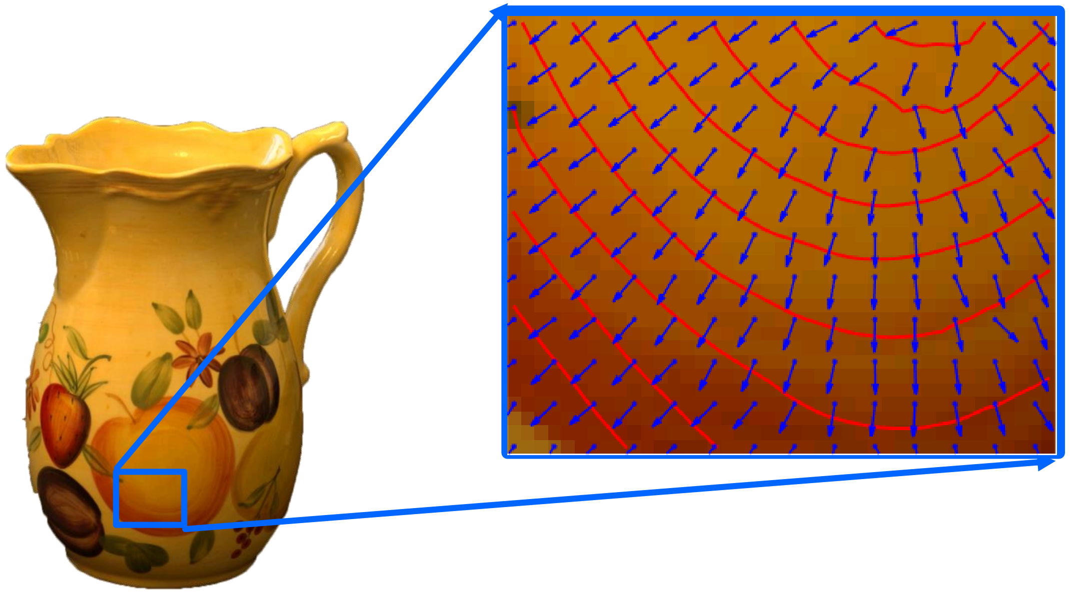
- Exploit polarimetric information for dense reconstruction:
  - Use geometric information to help resolve ambiguities of polarimetric information
  - Use polarimetric information to improve geometric information



Polarimetric Multiple View Stereo [CVPR'17]

- Iso-depth contour tracing: Propagate reliable depth values along iso-depth contour
  1. Phase angle determine the projected surface normal direction (with π-ambiguity)
  2. From the normal, we can get iso-depth contour on which the pixels have with the same depth
  3. Propagate sparse depth values along iso-depth contour

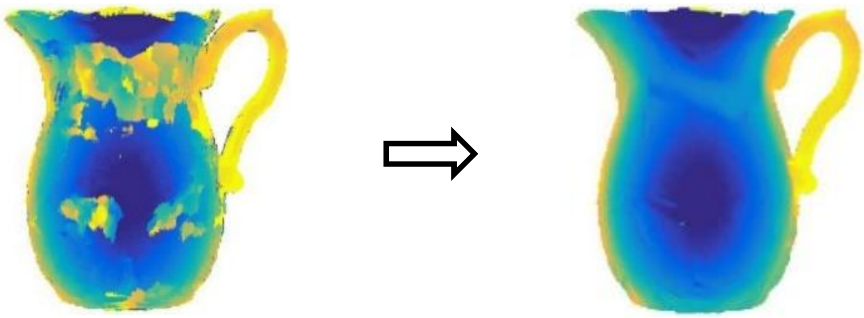




Polarimetric Multiple View Stereo [CVPR'17]

- Per-frame depth optimization

$$\sum_{(x,y)\in\mathcal{P}} \underbrace{E_p\big(d(x,y)\big)}_{\text{constraint from azimuth angles}} + \gamma \underbrace{E_d\big(d(x,y)\big)}_{\text{constraint from known 3D points}} + \underbrace{|\Delta d(x,y)|}_{\text{smoothness constraint}}$$



Polarimetric Multi-View Stereo

Supplementary Material

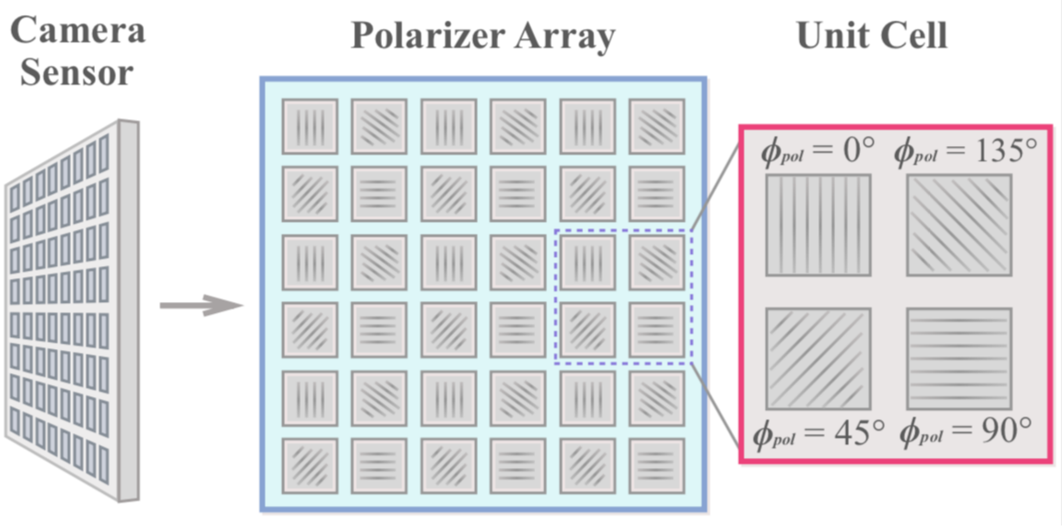
Paper ID 579

Polarimetric Dense Monocular SLAM [CVPR'18]

DSLR +
Polarizer Filters

Rotate the polarizer filter manually

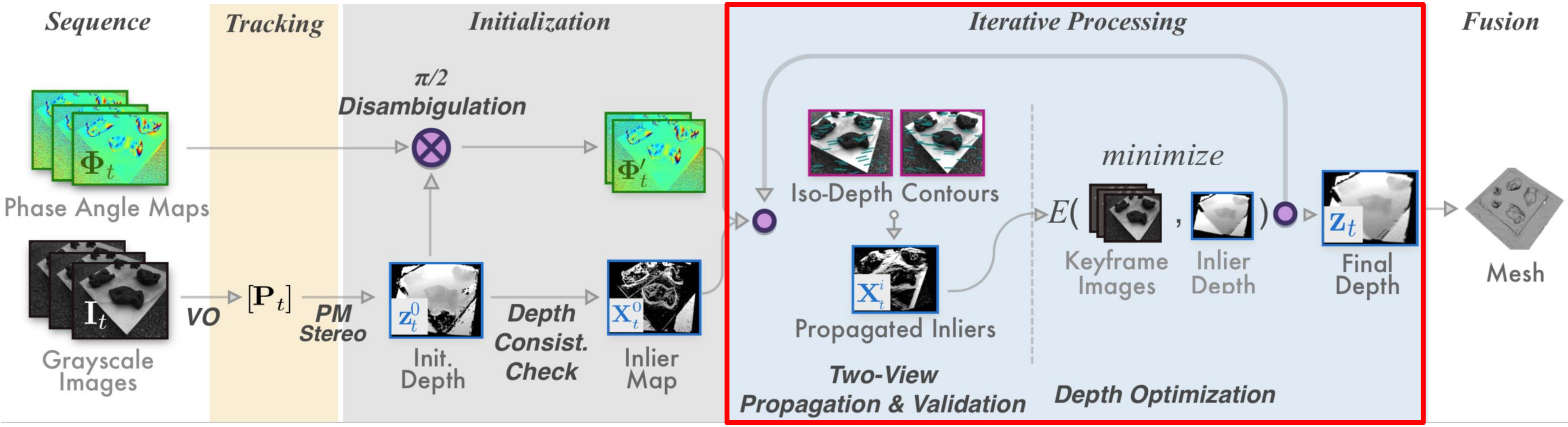
Polarization camera



Sensor Structure

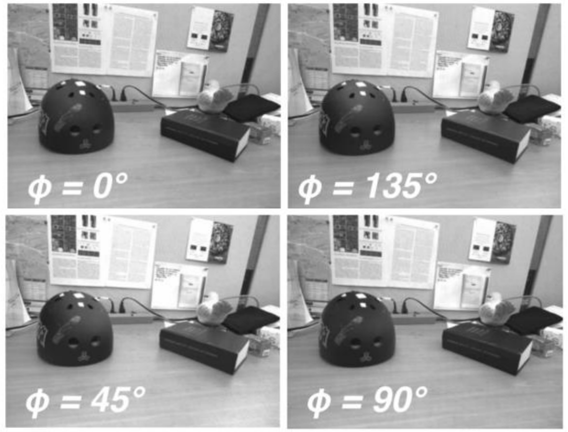
video with multiple polarized image

Polarimetric Dense Monocular SLAM [CVPR'18]

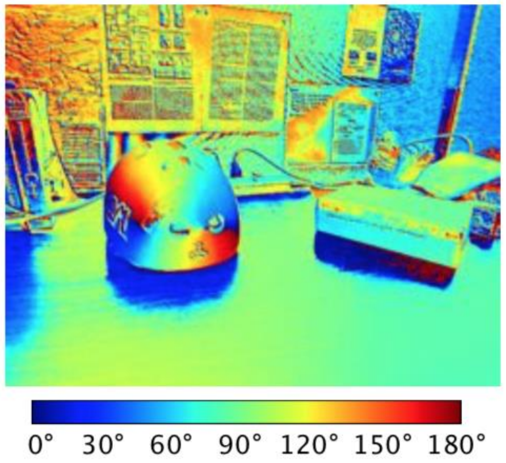


Polarimetric Dense Monocular SLAM [CVPR’18]

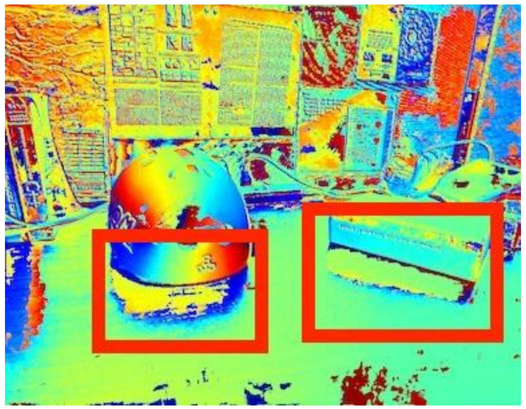
- Phase angle disambiguation: Using rough depth to solve the $\pi/2$-ambiguity
  - Intuition: The correct iso-contour should have less depth variation.
  - Strategy: Trace two local contours, select the one with less depth variance.



Captured Polarized Images



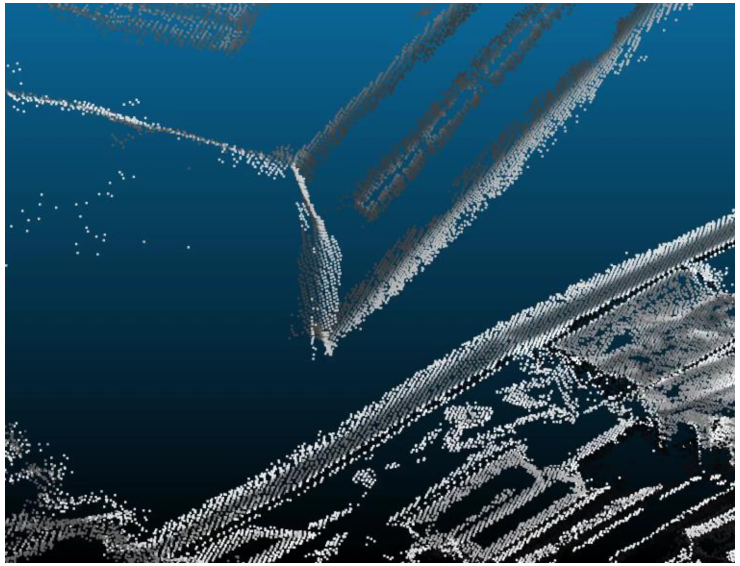
Phase Angle Map



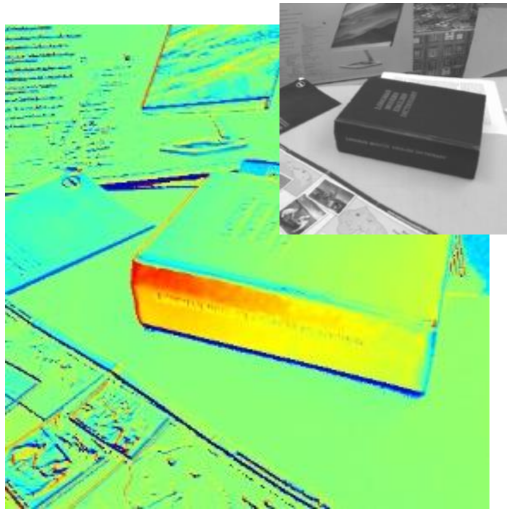
Disambiguation Results

Polarimetric Dense Monocular SLAM [CVPR'18]

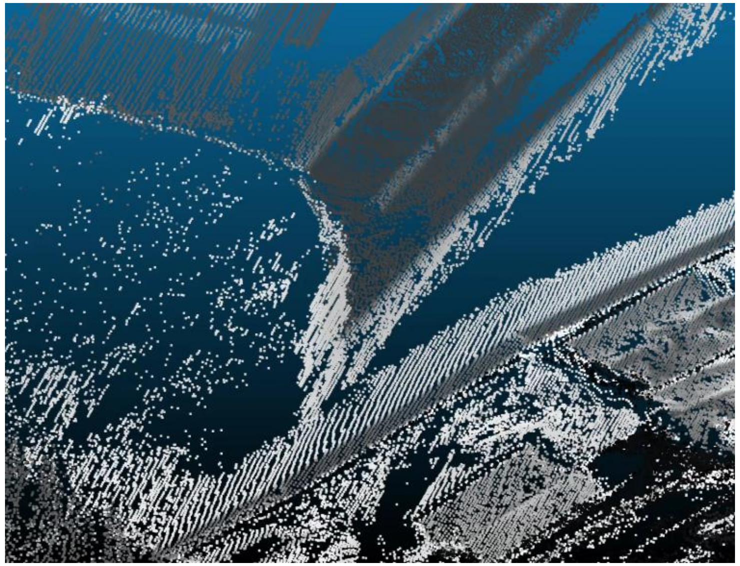
- Depth propagation along contours
  - Issue: wrong propagation caused by noisy 3D points
  - Solution: Two-View propagation and validation



Inlier Points

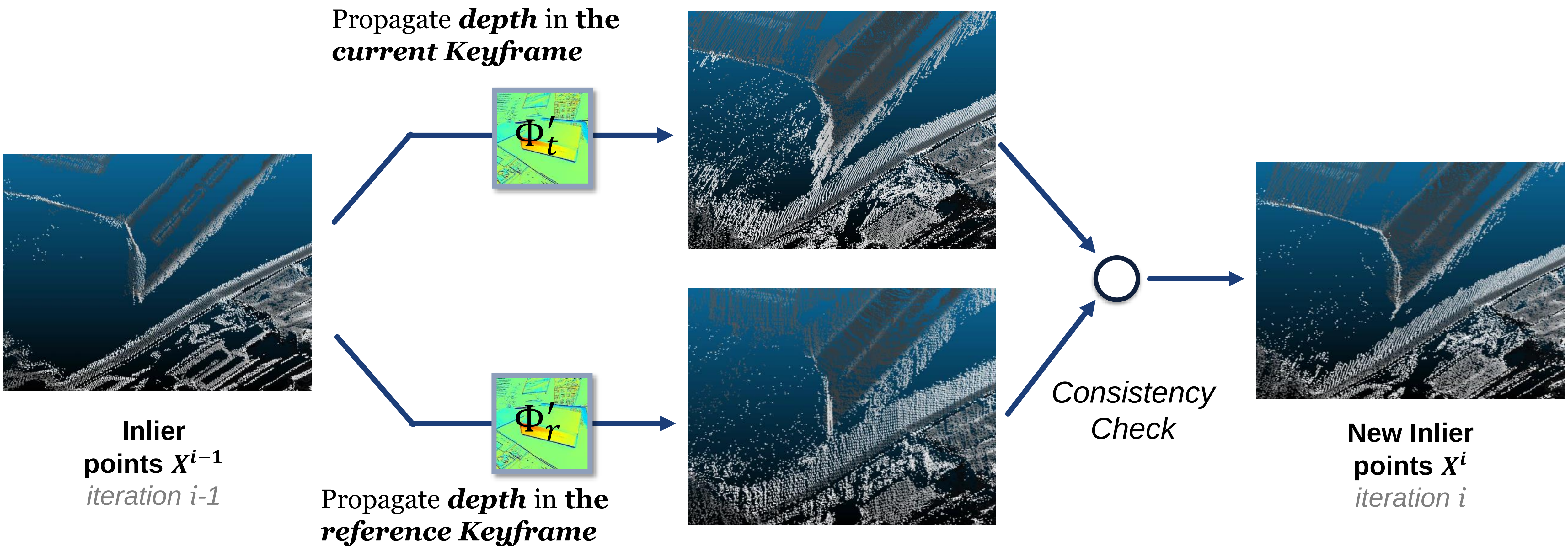


Phase map



Propagated Points (Using Single-View)

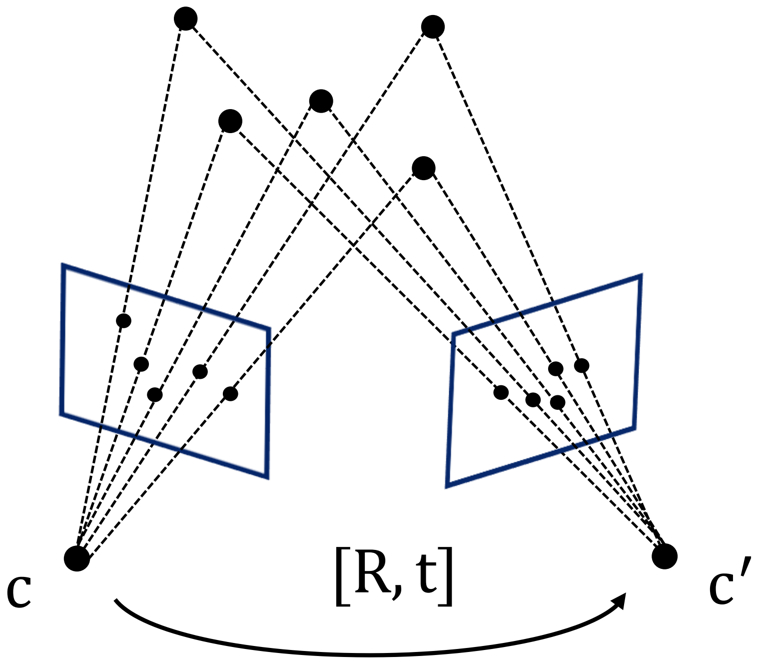
Polarimetric Dense Monocular SLAM [CVPR'18]



SFU SIMON FRASER UNIVERSITY
ENGAGING THE WORLD

Traditional Relative Pose Estimation

- 5-point algorithm:



Challenges

Surface normal estimation from polarization is hard:

- Refractive distortion: Zenith angle estimation requires the knowledge of the refractive index
- Azimuthal ambiguity: The estimation of the azimuthal angle has π-ambiuity

$$I(\phi_{pol}) = \frac{I_{max} + I_{m}}{2} \quad)$$

4^n possibilities given n pairs of correspondences.

$\varphi = \phi$ or $\varphi = \phi + \pi$

- Mixed reflection in real environment.

Polarimetric Relative Pose Estimation [ICCV'19]

Two-point relative pose estimation:

- Step 1. Solve the relative rotation:

$$\min_{R \in SO(3)} \|Rv_1 - v_1'\|^2 + \|Rv_2 - v_2'\|^2$$

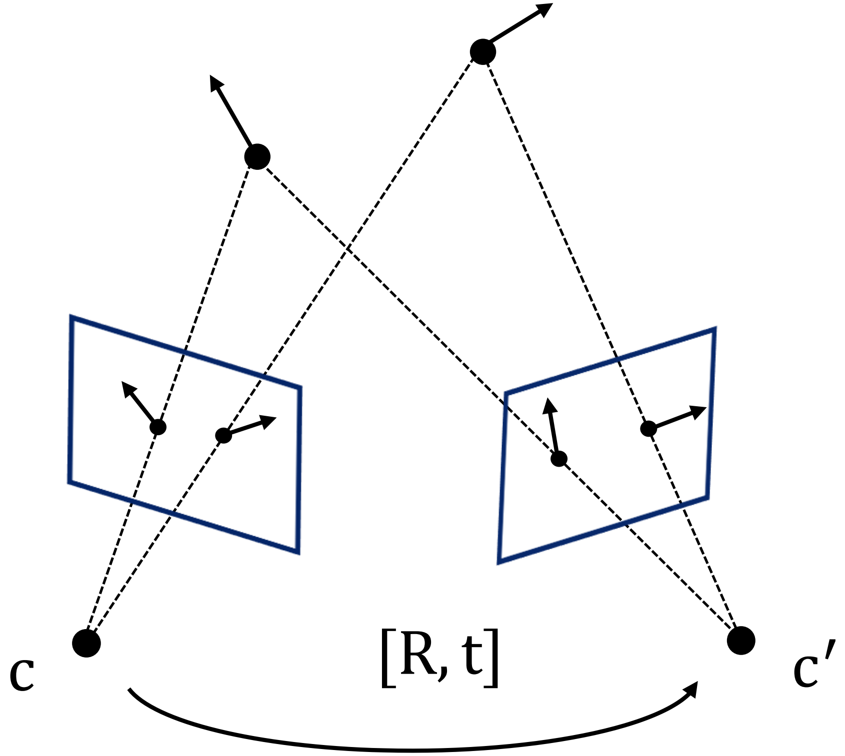
$$\Rightarrow \quad R = U\,\mathrm{diag}\left(1,1,\det\left(UV^T\right)\right)V^T$$

$$U\Sigma V^T = v_1' v_1^T + v_2' v_2^T$$

- Step 2. Solve the relative translation:

$$x_i' \cdot (t \times Rx_i) = t \cdot (Rx_i \times x_i') = 0, i = 1,2$$

$$\Rightarrow \quad t = (Rx_1 \times x_1') \times (Rx_2 \times x_2')$$



- Step 3. Hypothesis validation to choose the one which has the largest consensus.

Polarimetric Relative Pose Estimation [ICCV'19]

Resolving the azimuth angle ambiguity

- We can recover the correct azimuth angles (φ, φ') by considering the alignment error:

$$\|\mathrm{R}\mathrm{v}(\varphi) - \mathrm{v}'(\varphi')\|^2$$

For each correspondence we only need to check four cases:

$$(\phi, \phi'), (\phi + \pi, \phi'), (\phi, \phi' + \pi) \text{ and } (\phi + \pi, \phi' + \pi),$$

and select the one which minimizes the alignment residual.

Polarimetric Relative Pose Estimation [ICCV'19]

Polarimetric two-view local refinement: Optimizing jointly over the relative pose and the refractive indices:

$$\min_{\mathrm{R} \in SO(3), \mathrm{t} \in \mathbb{S}^2, \{n_i\}} f_{samp}(\mathrm{R}, \mathrm{t}) + f_{norm}(\mathrm{R}, \{n_i\}) + f_{prior}(\{n_i\}) \,,$$

where $f_{samp}(\mathrm{R}, \mathrm{t})$ is the standard squared Sampson loss,

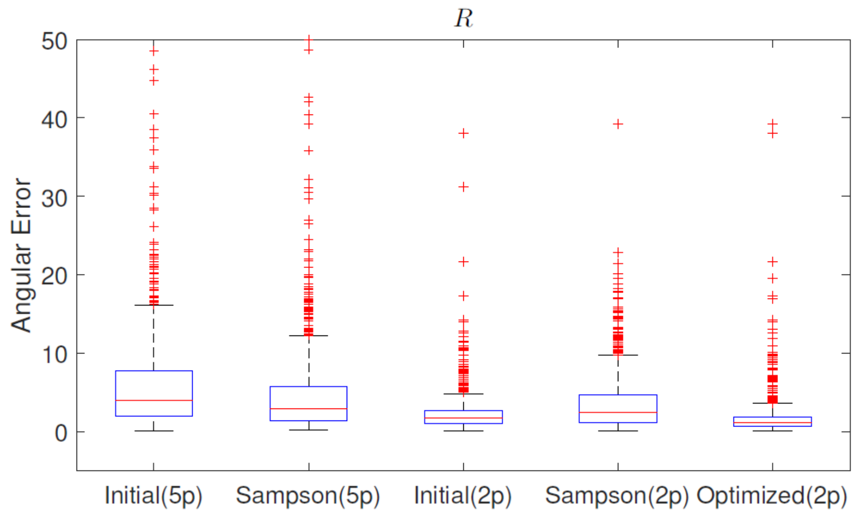
$$f_{norm}(\mathrm{R}, \{n_i\}) = \gamma_{normal} \sum_{i=1}^{m} \|\mathrm{R}\mathrm{v}_i(n_i) - \mathrm{v}_i'(n_i)\|^2 \,,$$

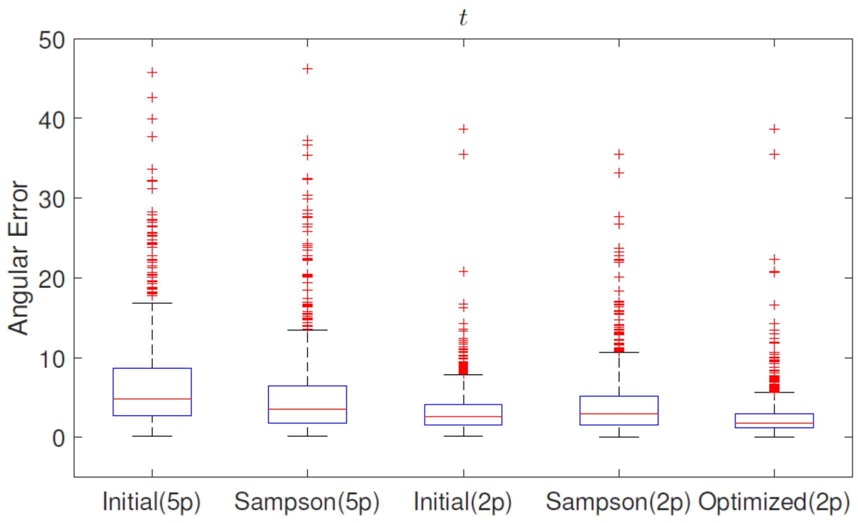
$$f_{prior}(\{n_i\}) = \gamma_{prior} \sum_{i=1}^{m} (n_i - n_i^0)^2 .$$

Polarimetric Relative Pose Estimation [ICCV'19]

- Comparison with 5-point algorithm on synthetic data

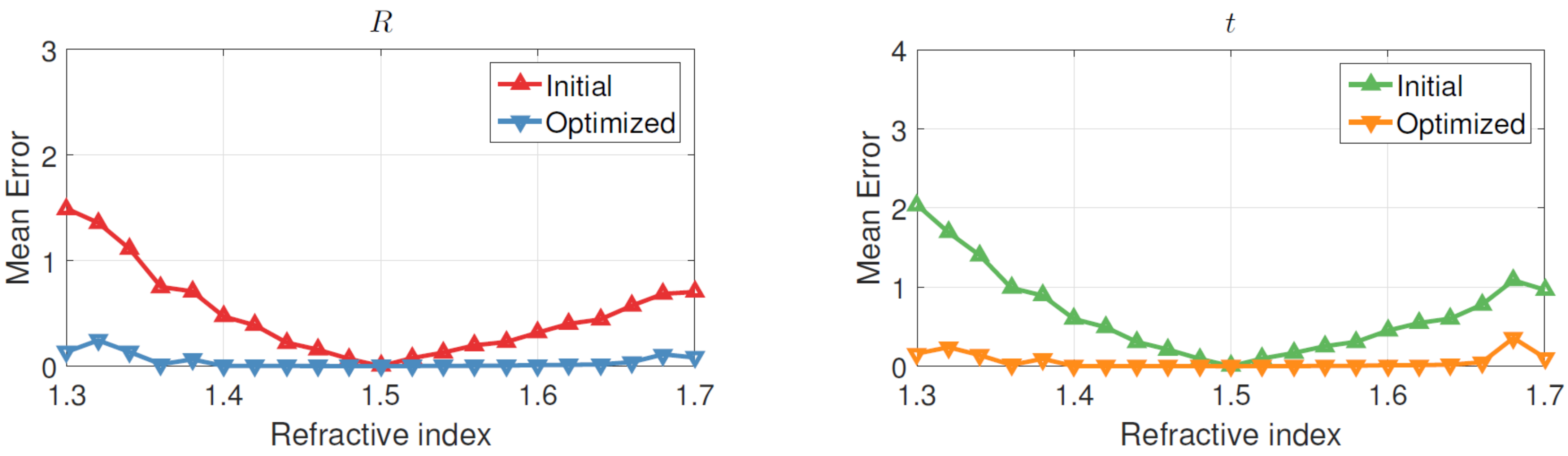
	5-point		Ours		
	Initial	Sampson	Initial	Sampson	Optimized
R_{err}	6.10	4.95	2.30	3.59	**1.80**
t_{err}	9.30	7.37	3.25	4.08	**2.52**





Polarimetric Relative Pose Estimation [ICCV'19]

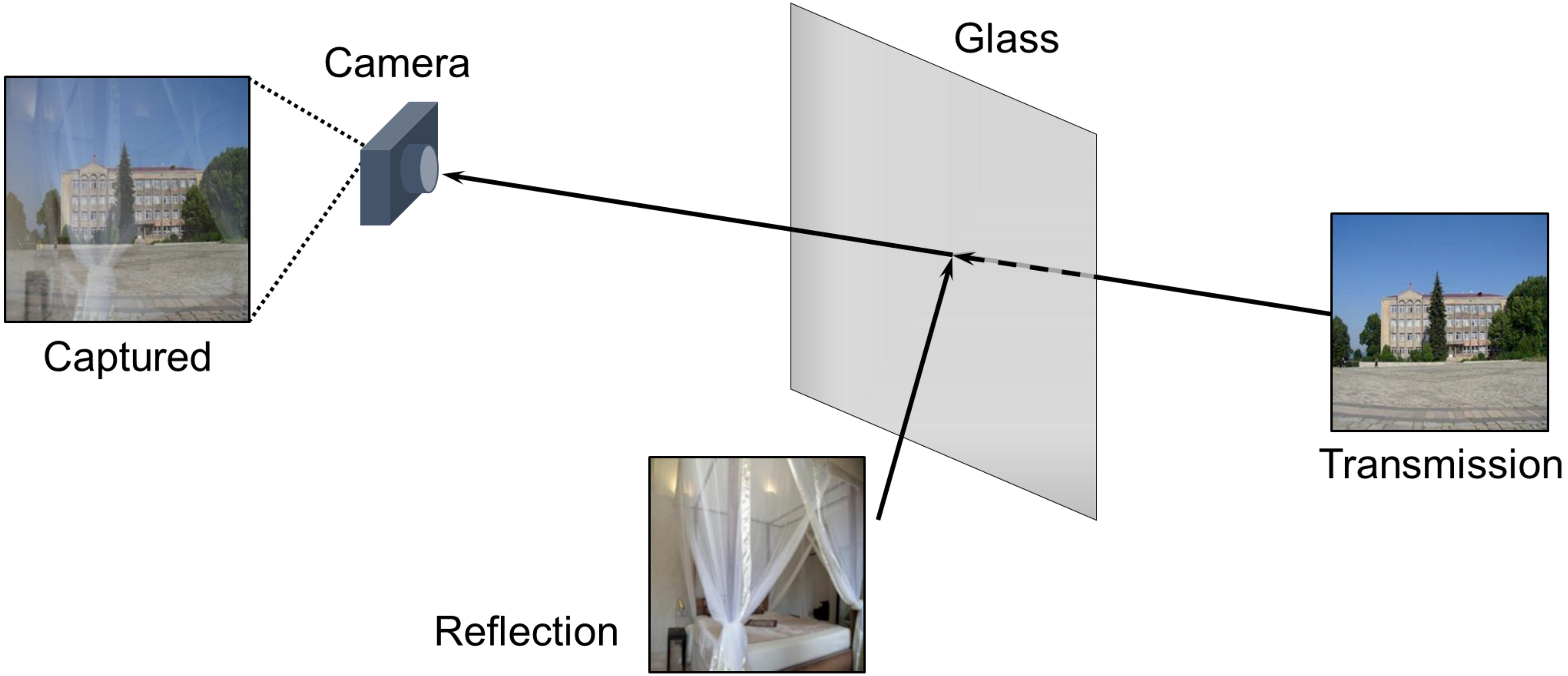
- Performance with different initial guess of the refractive index



Outline

- Background
- Polarimetric 3D Reconstruction
  - Polarimetric Multiple-View Stereo [CVPR’2017]
  - Poalrimetric Dense Monocular SLAM [CVPR’2018]
  - Poalrimetric Relative Pose Estimation [ICCV’2019]
- Polarimetric Reflection Separation [NeurIPS’2019]
- Conclusion

Reflection Separation



Reflection Separation

- An ill-posed problem

Captured

I

Reflection

I_r

Transmission

I_t

Previous Solutions

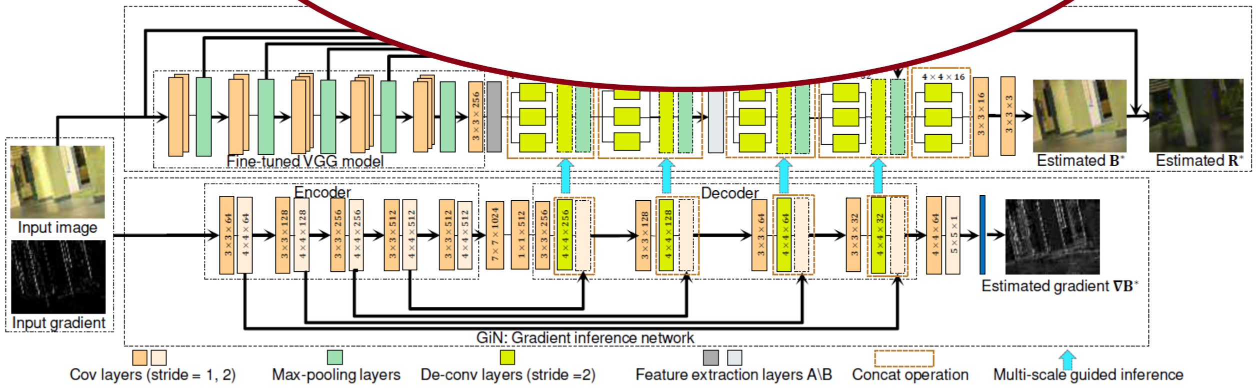
Additional Priors

- Gradient sparsity priors

  [Levin et al. 07] [W… al. 18]

-

Violate in real-world scenarios



[Wan et al. 18]

Additional Input

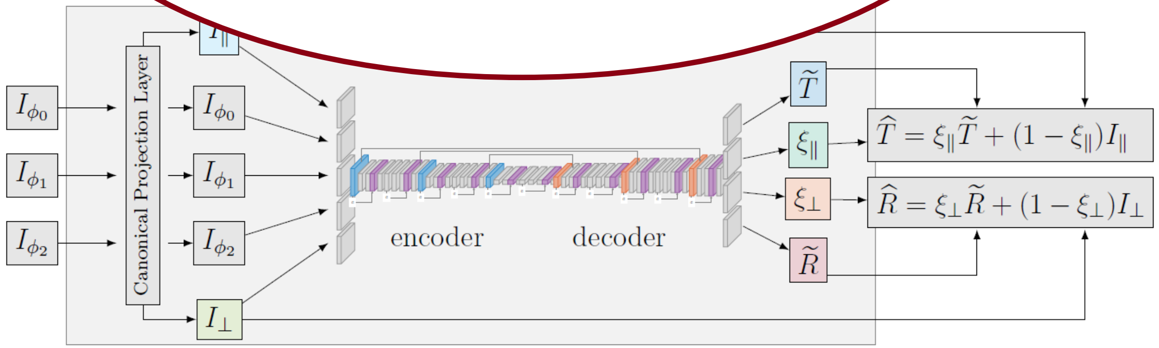
- Different viewpoints

  [Gai et al. 12] […] [Xue et al. 15]

- D…

  …8]

Complicated capturing operations



[Wieschollek et al. 18]

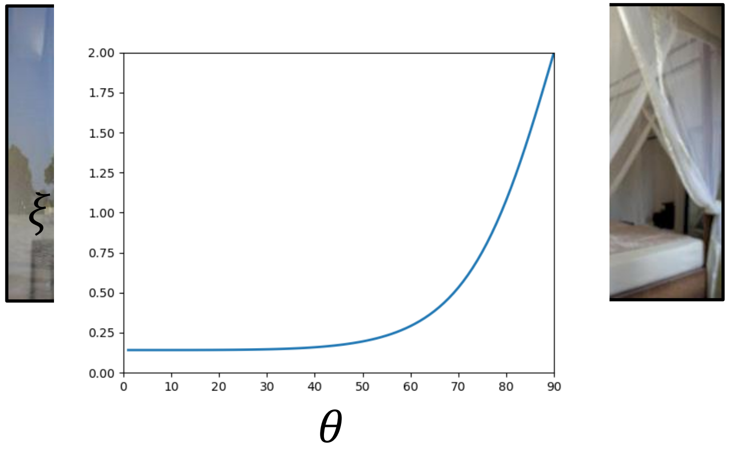
We design an end-to-end neural network which takes a pair of (un)polarized images for reflection separation based on a new physical image formation model.

New Setup: (un)polarized images

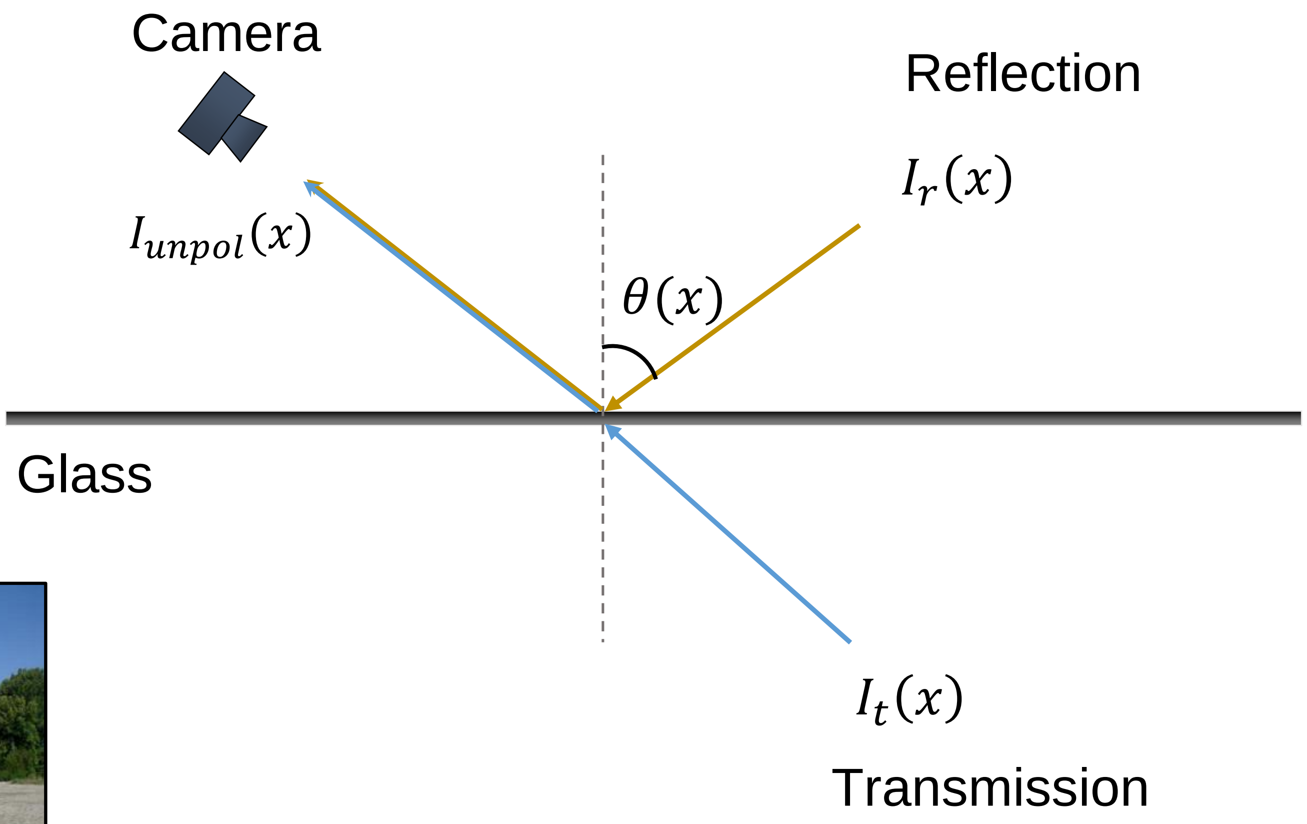
Without polarizer
in front of the camera

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

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



I_t

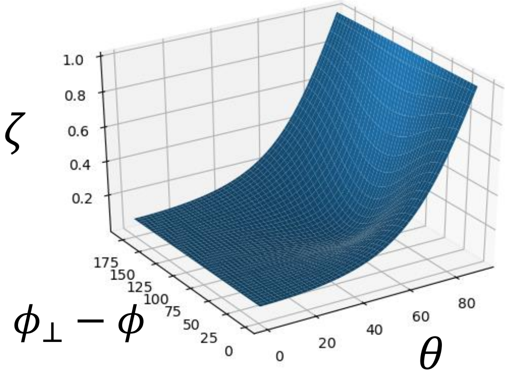


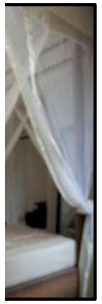
New Setup: (un)polarized images

With polarizer
in front of the camera

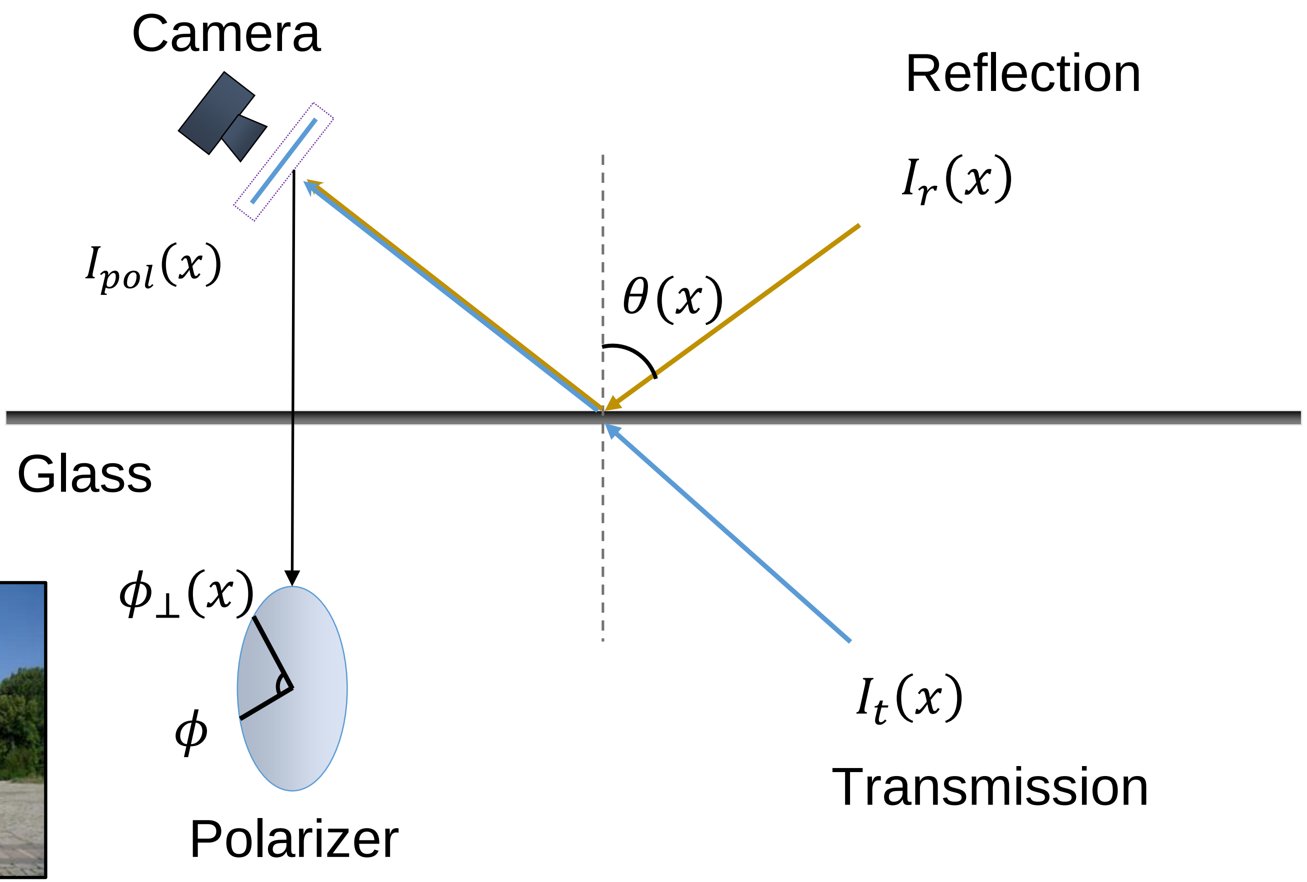
$$I_{pol}(x) = I_r\,(x) \cdot \frac{\zeta(x)}{2} + I_t\,(x) \cdot \frac{1-\zeta(x)}{2}$$

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





I_t



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:

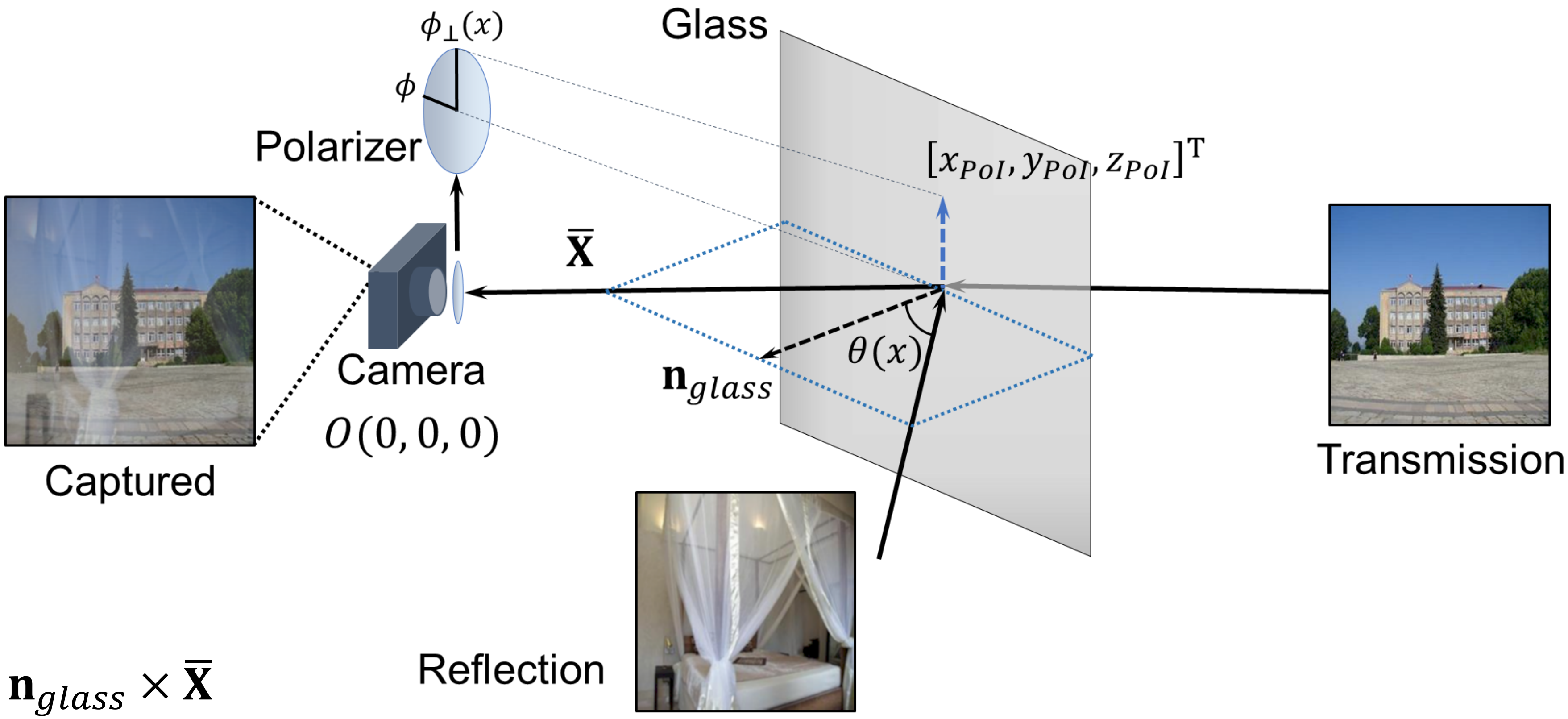
$$I_{pol}(x) = I_r(x) \cdot \frac{\zeta(x)}{2} + I_t(x) \cdot \frac{1 - \zeta(x)}{2}$$

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

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

Physical Image Formation Model

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

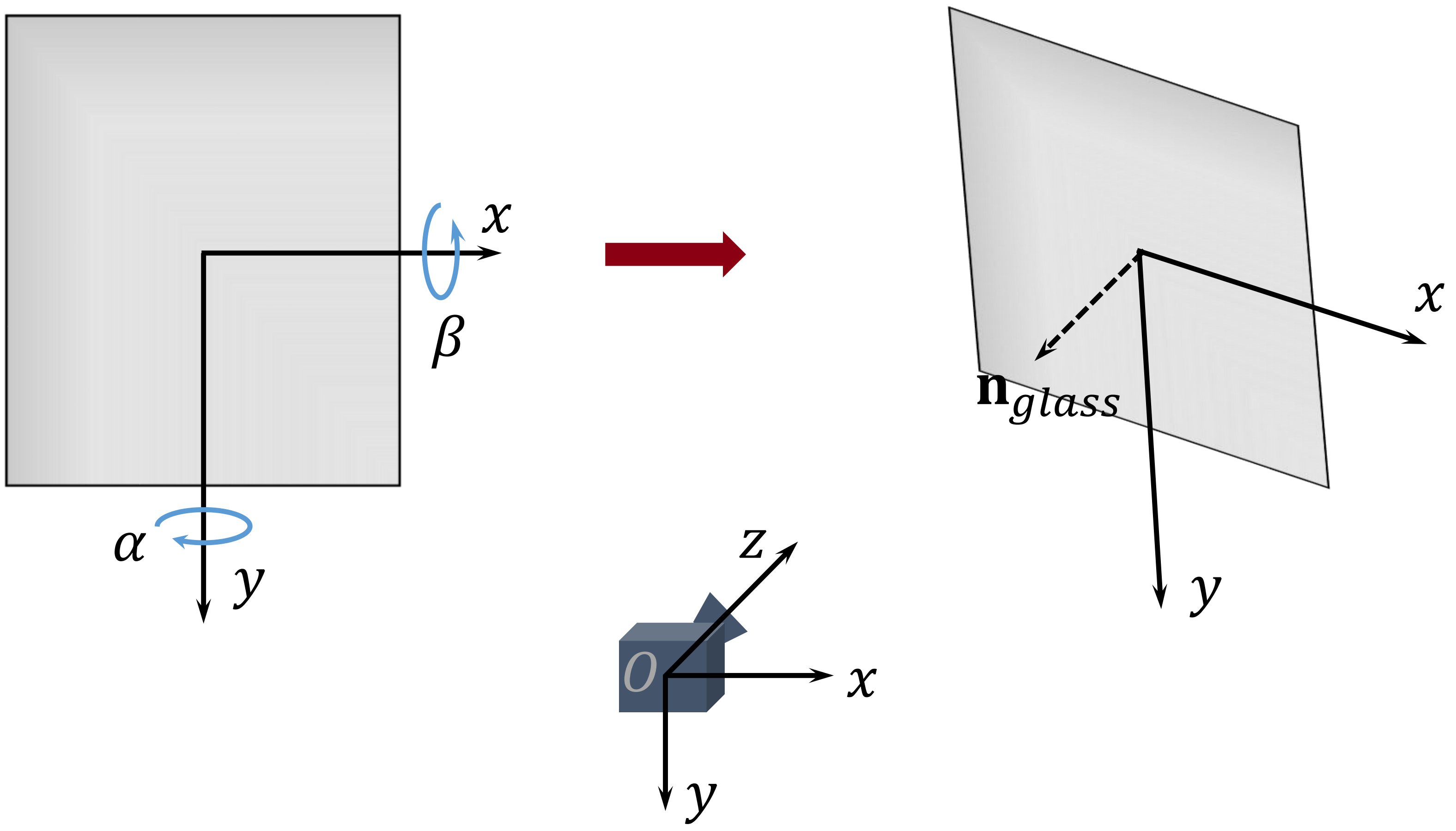


$$\phi_\perp(x) = \arctan\frac{y_{PoI}}{x_{PoI}}$$

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

ETH zürich

Physical Image Formation Model



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

Physical Image Formation Model

Without polarizer:

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

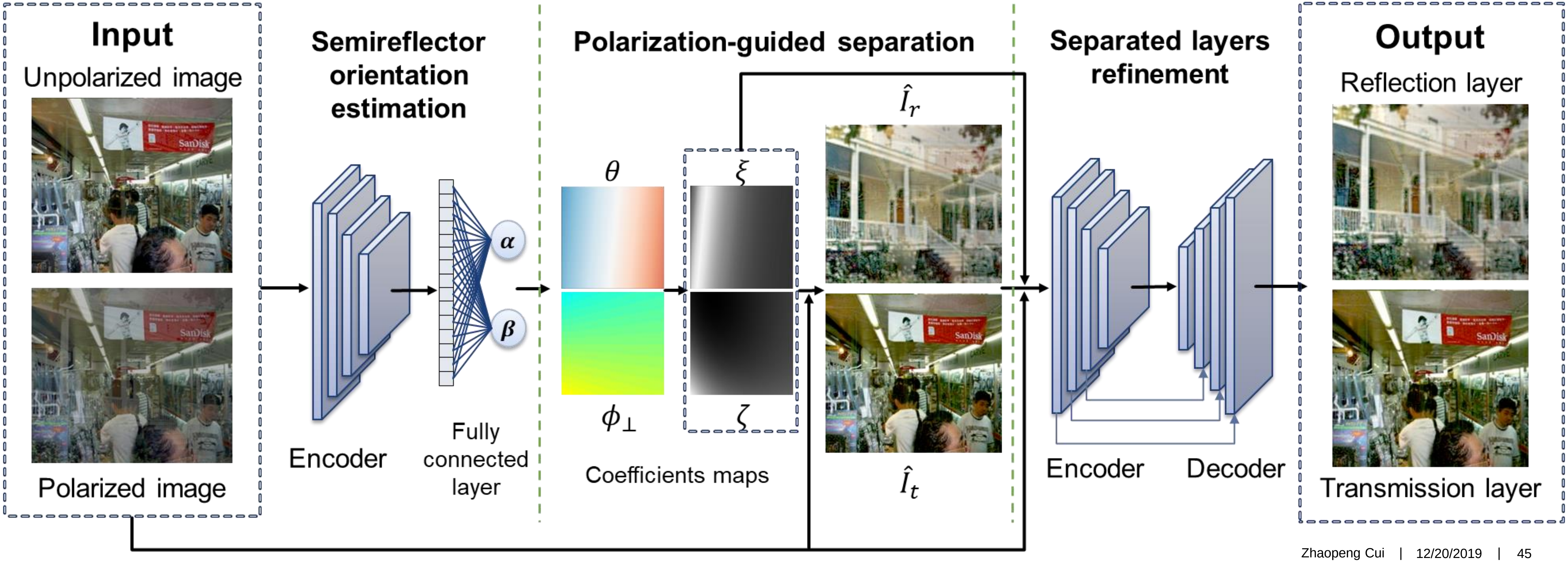
With polarizer:

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

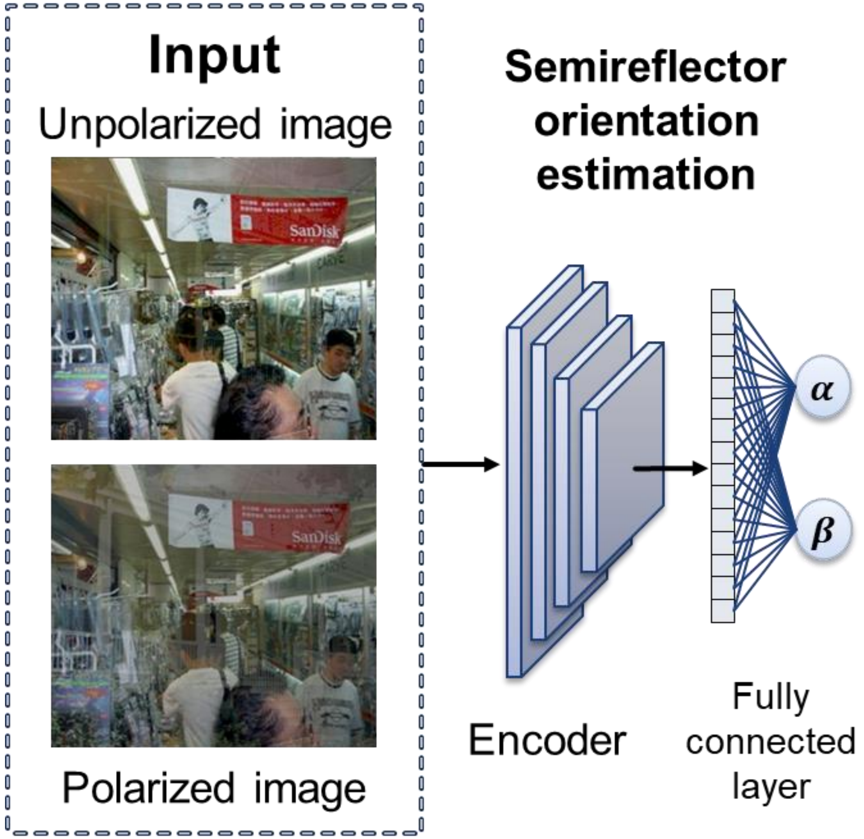
$$\left.\begin{array}{l} I_{unpol}(x), I_{pol}(x) \\ \theta(x), \phi_{\perp}(x) \end{array}\right] \Rightarrow I_t(x),\ I_r(x)$$

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

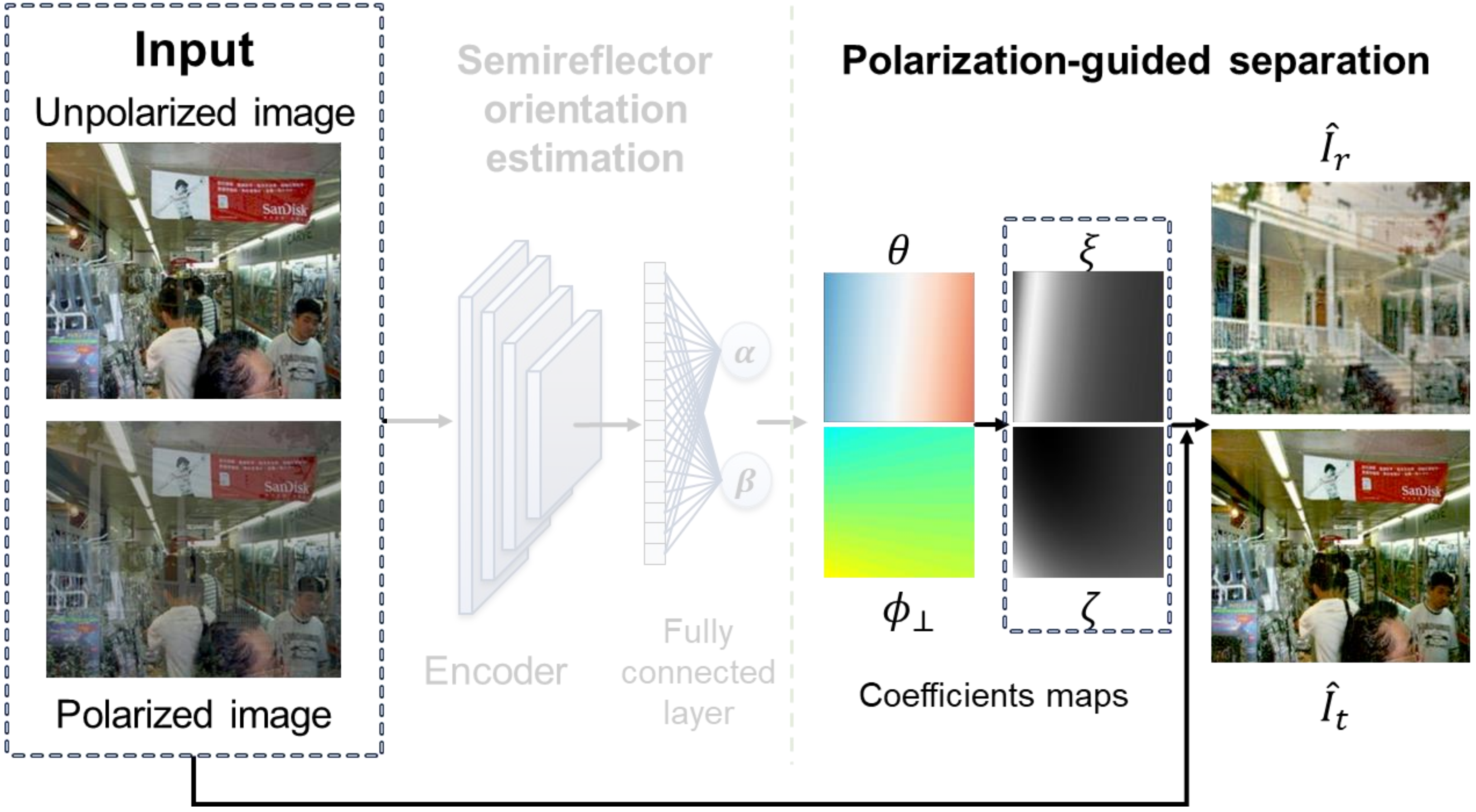
Reflection Separation Network



Reflection Separation Network



Reflection Separation Network



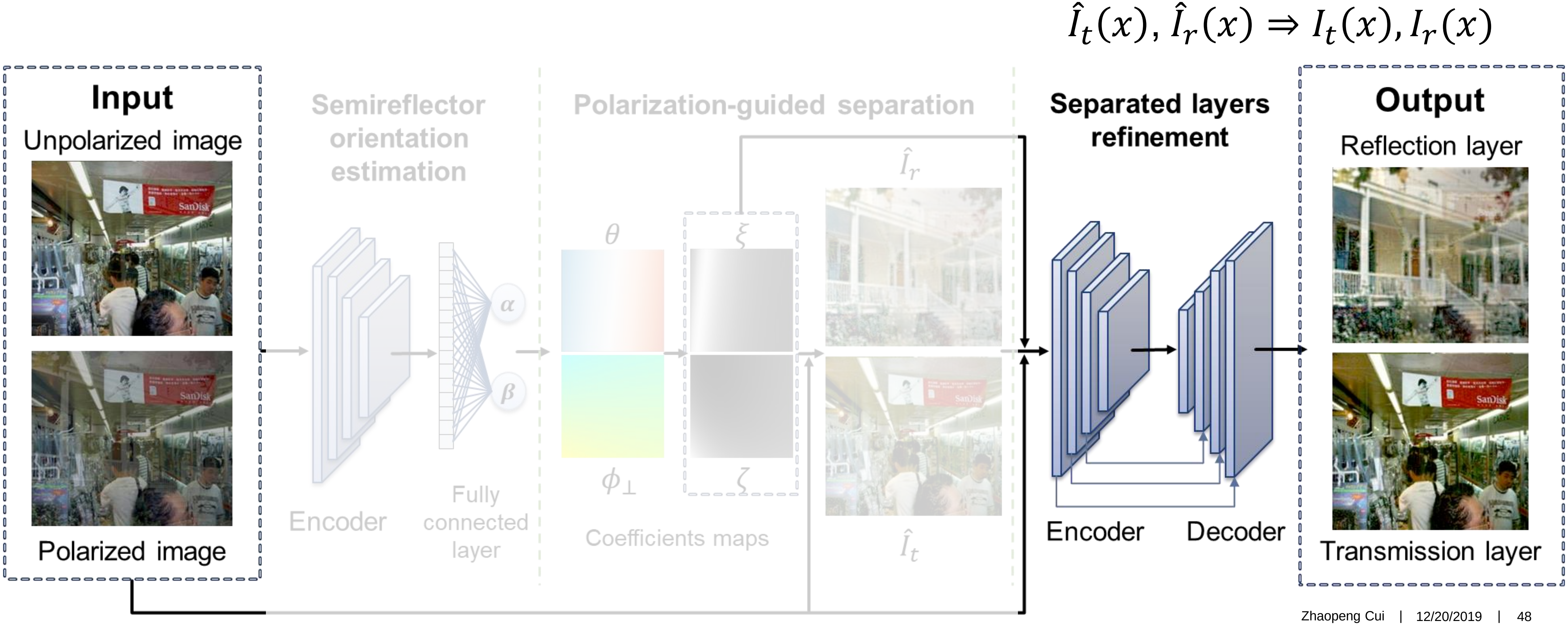
$$\theta(x) = \operatorname{arcos}(|\mathbf{n}_{glass} \cdot \bar{\mathbf{X}}|)$$

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

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

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

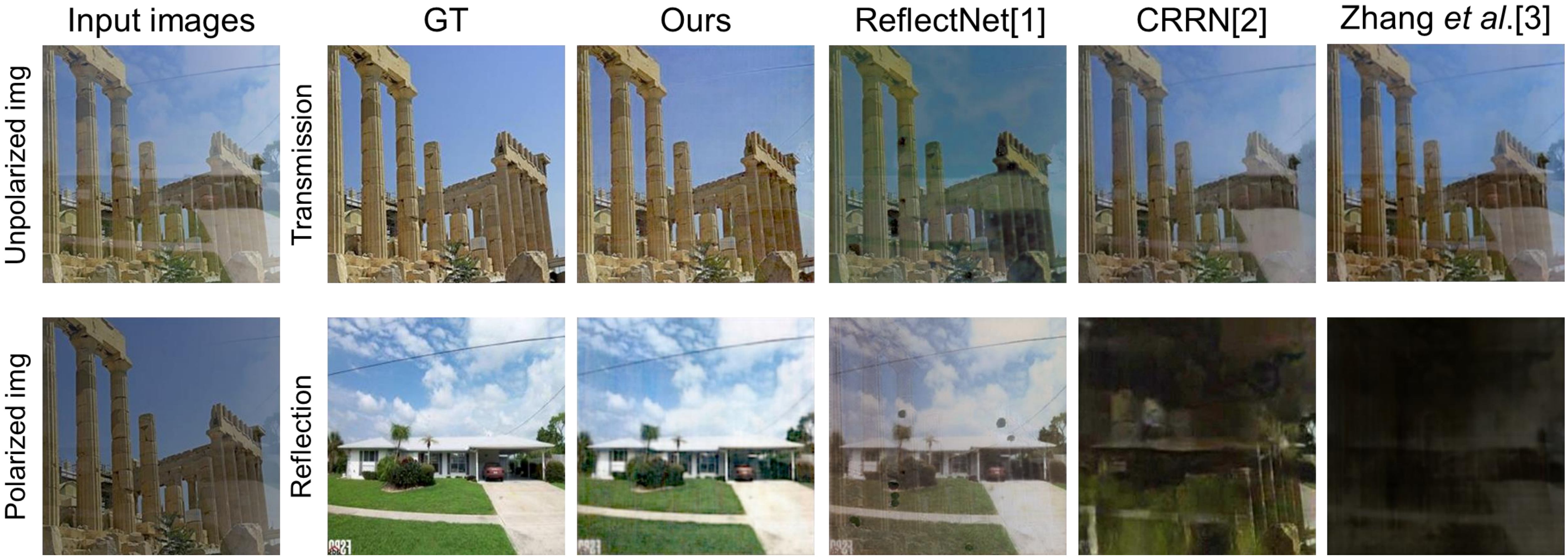
Reflection Separation Network



Evaluation on Synthetic Data

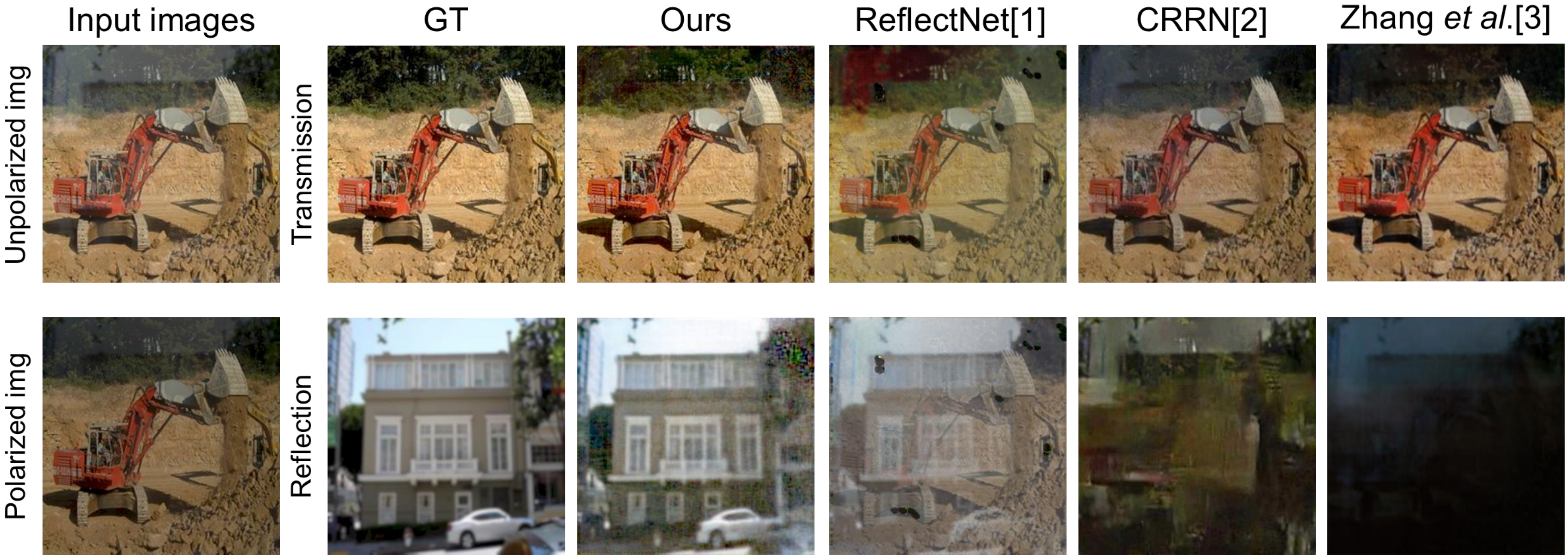
		Ours	Ours-Initial	ReflectNet-Finetuned	Ours-2% noise	Ours-8% noise	Ours-16% noise
Transmission	SSIM	**0.9708**	0.8324	0.9627	0.9691	0.9668	0.9619
	PSNR	**28.23**	21.61	27.52	28.08	27.31	27.17
Reflection	SSIM	**0.8953**	0.6253	0.8303	0.8785	0.8418	0.8022
	PSNR	**20.92**	13.90	18.50	20.53	19.18	18.26

Evaluation on Synthetic Data



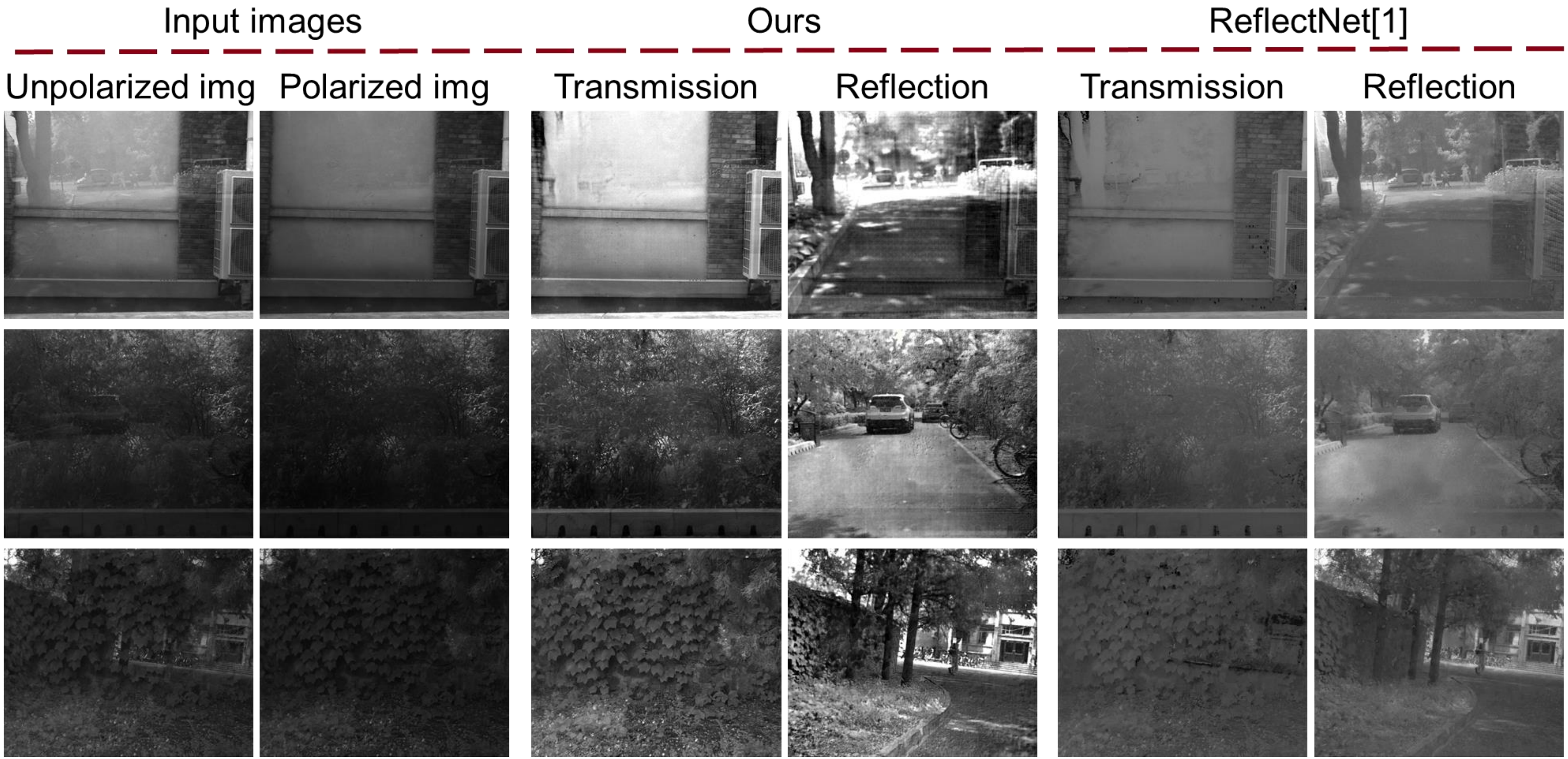
[1] P. Wieschollek, O. Gallo, J. Gu, and J. Kautz. Separating reflection and transmission images in the wild. In Proc. ECCV, 2018.
[2] R. Wan, B. Shi, L.-Y. Duan, A.-H. Tan, and A. C. Kot. CRRN: Multi-scale guided concurrent reflection removal network. In Proc. CVPR, 2018
[3] X. Zhang, R. Ng, and Q.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

Evaluation on 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

- Polarization conveys both geometric and physical cues of the surrounding environment.

- The encoded rough geometric information in polarization can contribute to 3D reconstruction.

- The polarization is helpful for image reflection separation.

Future Work

- The current physical model for polarization is ideal to some extent, and more complex model should be studied.

- Polarization can be applied to other vision tasks, including image segmentation, image dehazing, etc.

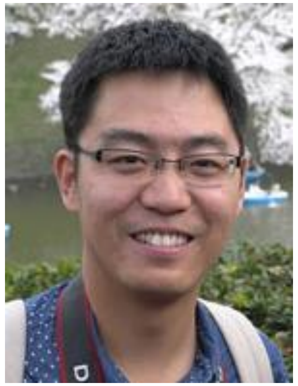
Collaborators

Marc Pollefeys
@ETH Zurich

Ping Tan
@SFU

Jinwei Gu
@SenseTime

Jan Kautz
@NVIIDA



Boxin Shi
@Peking University

Yasutaka Furukawa
@SFU

Viktor Larsson
@ETH Zurich

Luwei Yang
@SFU

Feitong Tan
@SFU

Youwei Lyu
@BUPT

Related work

- [1] Polarimetric Multi-View Stereo. Zhaopeng Cui, Jinwei Gu, Boxin Shi, Ping Tan, and Jan Kautz. CVPR, 2017.
- [2] Polarimetric Dense Monocular SLAM. Luwei Yang*, Feitong Tan*, Ao Li, Zhaopeng Cui, Yasutaka Furukawa, and Ping Tan. CVPR, 2018.
- [3] Polarimetric Relative Pose Estimation. Zhaopeng Cui, Viktor Larsson, and Marc Pollefeys. ICCV, 2019.
- [4] Reflection Separation using a Pair of Unpolarized and Polarized Images. Youwei Lyu*, Zhaopeng Cui*, Si Li, Marc Pollefeys, and Boxin Shi. NeurIPS, 2019.

Thanks

Q&A