Learning to dehaze with polarization

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Background

Original scene radiance $\mathbf{R}$

Haze

(atmospheric scattering)

Hazy image $\mathbf{I}$

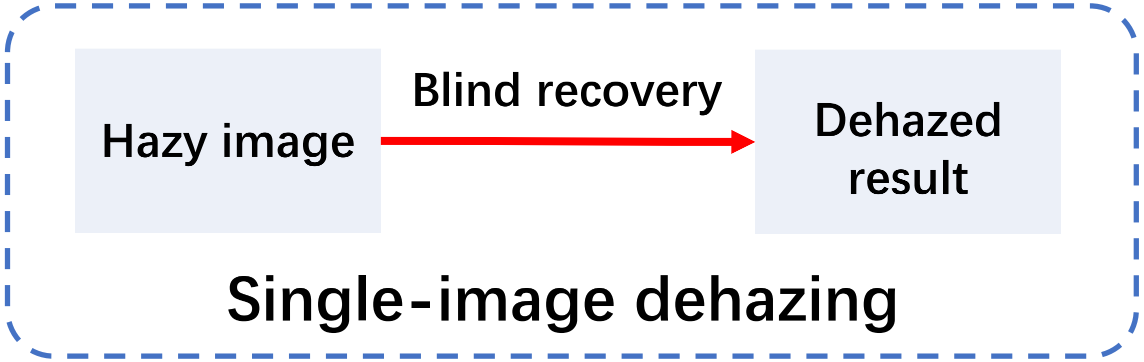
Transmitted light $\mathbf{T}$

$+$

Airlight $\mathbf{A}$

A hazy image contains two unknown components.

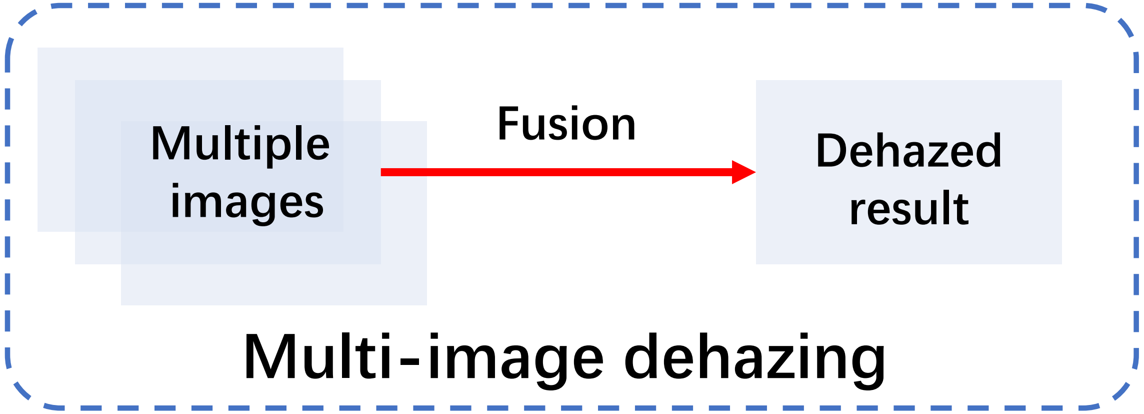
Two kinds of dehazing methods



Blindly recover the original scene radiance

- **Numerical optimization** [He PAMI10]
- **CNN** [Dong CVPR20]
- **GAN** [Deng ECCV20]

Pros: only require a single shot
Cons: very ill-posed and bad generalization ability



Capture multiple images

- **under different weather conditions** [Nayar PAMI03]
- **from different viewpoints** [Pang CVPR20]
- **using different kind of camera (RGB+NIR)** [Feng ICIP13]

Pros: less ill-posed and good generalization ability
Cons: require multiple shots

Polarization: making dehazing more robust and convenient

Hazy image $\mathbf{I}$

Polarization camera

captured in a single shot

Polarized images $\mathbf{I}_{\alpha^{(1,2,3)}}$

Polarization-based dehazing methods

[Schechner CVPR01]

[Namer OE09]

[Fang OE14]

...

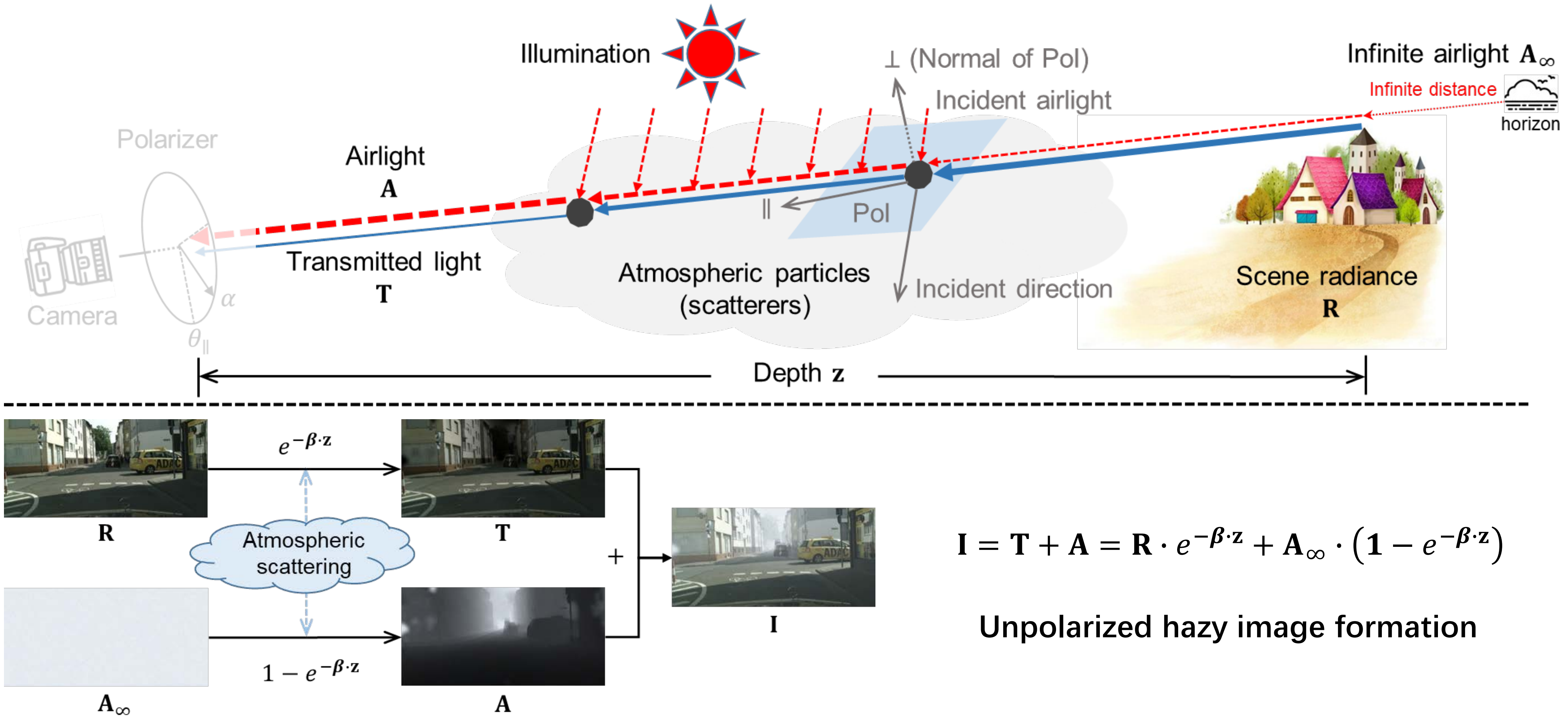
Dehazed result

Still not robust enough!

However, they

- **assume the transmitted light is not significantly polarized**
- **require sky regions to estimate the infinite airlight and DoP**
- **cannot handle the spatially-variant real-world scattering**
- **ignore the semantic and contextual information**

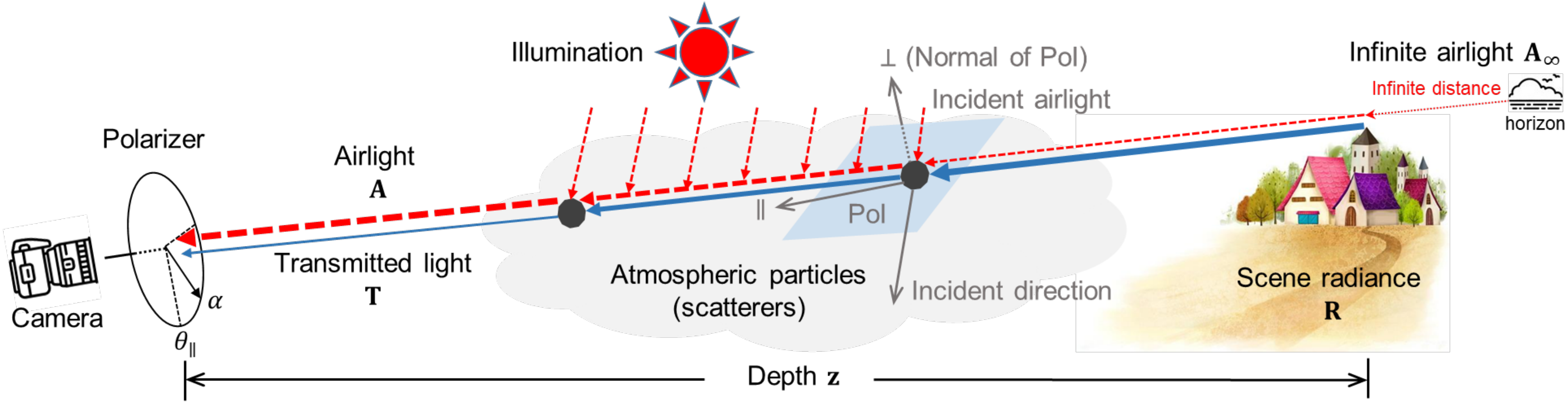
A generalized physical image formation model



$$\mathbf{I} = \mathbf{T} + \mathbf{A} = \mathbf{R} \cdot e^{-\boldsymbol{\beta}\cdot\mathbf{z}} + \mathbf{A}_\infty \cdot \left(1 - e^{-\boldsymbol{\beta}\cdot\mathbf{z}}\right)$$

Unpolarized hazy image formation

A generalized physical image formation model



Decompose based on whether they are parallel or perpendicular to the PoI:

$$\mathbf{I} = \mathbf{I}^\perp + \mathbf{I}^\parallel \qquad \mathbf{T} = \mathbf{T}^\perp + \mathbf{T}^\parallel \qquad \mathbf{A} = \mathbf{A}^\perp + \mathbf{A}^\parallel$$

Degree of polarization (DoP):

$$\mathbf{P} = \frac{\mathbf{I}^\perp - \mathbf{I}^\parallel}{\mathbf{I}} \qquad \mathbf{P}_T = \frac{\mathbf{T}^\perp - \mathbf{T}^\parallel}{\mathbf{T}} \qquad \mathbf{P}_A = \frac{\mathbf{A}^\perp - \mathbf{A}^\parallel}{\mathbf{A}}$$

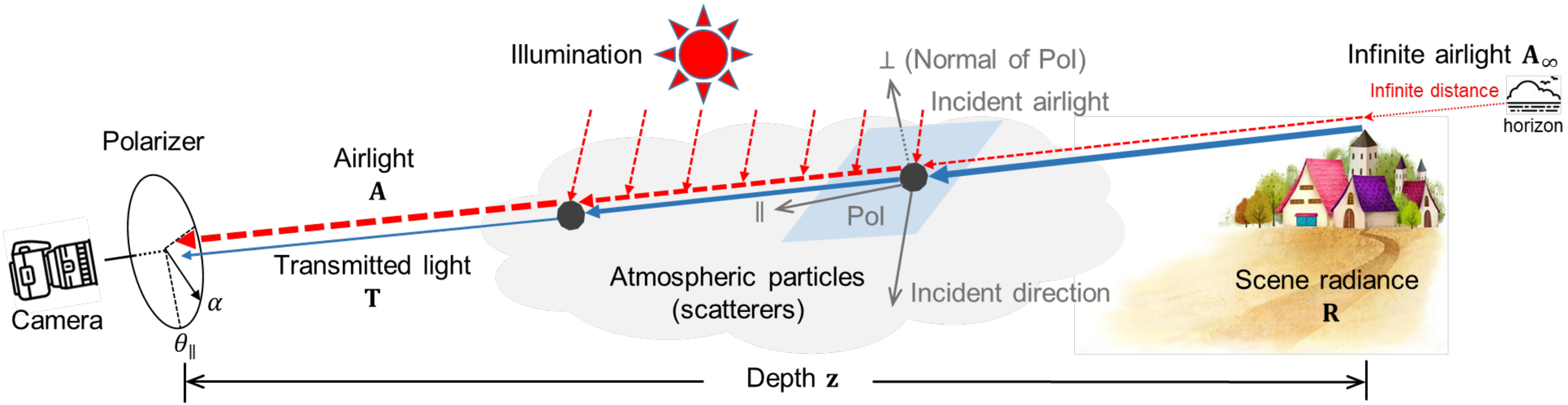
$\mathbf{P}$

$\mathbf{P}_T$

$\mathbf{P}_A$

Semantic segmentation map

A generalized physical image formation model



when placing a polarizer with polarization angle α:

$$\mathbf{I}_\alpha = \frac{\mathbf{I}\cdot\left(\mathbf{1}-\mathbf{P}\cdot\cos\left(2(\alpha-\boldsymbol{\theta}_\parallel)\right)\right)}{\mathbf{2}}$$

Malus' law

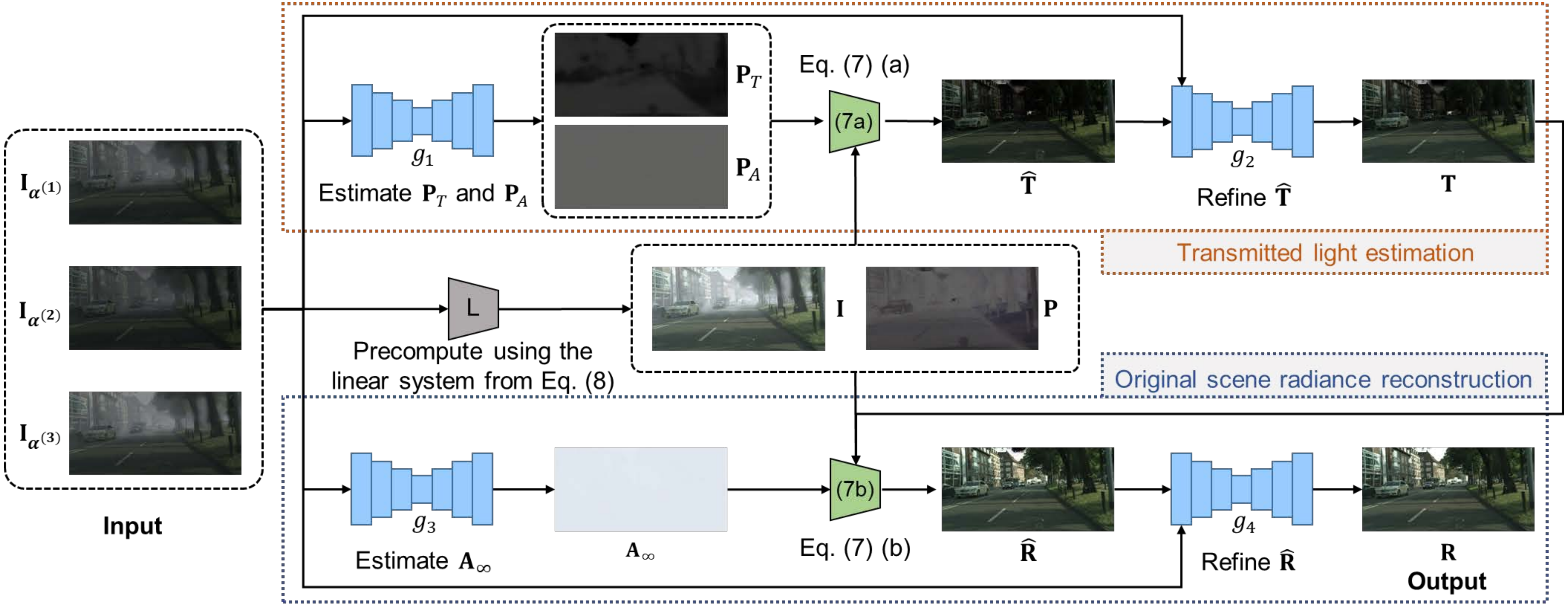
the two components:

$$\begin{cases} \mathbf{A}_\alpha = \dfrac{\mathbf{A}\cdot\left(\mathbf{1}-\mathbf{P}_A\cdot\cos\left(2(\alpha-\boldsymbol{\theta}_\parallel)\right)\right)}{\mathbf{2}} \\ \mathbf{T}_\alpha = \dfrac{\mathbf{T}\cdot\left(\mathbf{1}-\mathbf{P}_T\cdot\cos\left(2(\alpha-\boldsymbol{\theta}_\parallel)\right)\right)}{\mathbf{2}} \end{cases}$$

The relationship among $\mathbf{I}$, $\mathbf{T}$, and $\mathbf{A}$ are determined by $\mathbf{P}$, $\mathbf{P}_T$, and $\mathbf{P}_A$:

$$\mathbf{I}\cdot\mathbf{P} = \mathbf{T}\cdot\mathbf{P}_T + \mathbf{A}\cdot\mathbf{P}_A$$

Polarization-based dehazing pipeline: an overview

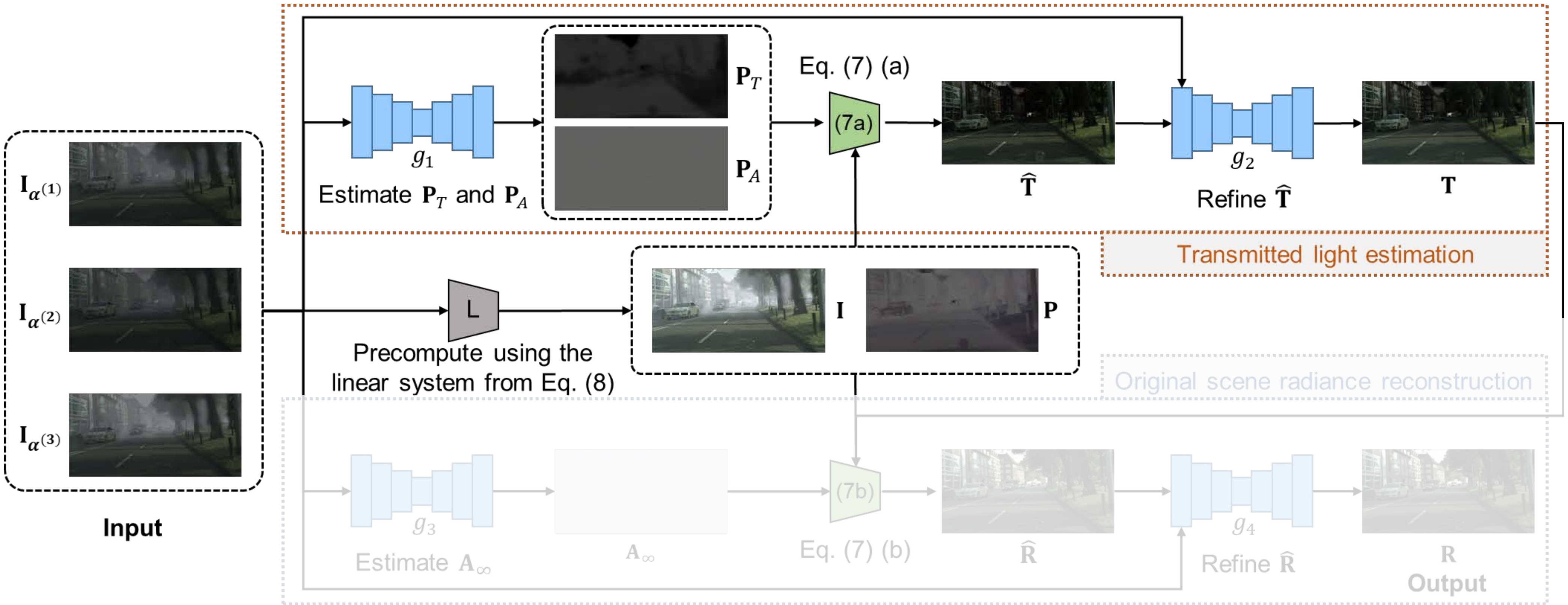


$$\begin{cases} \mathbf{I} = \mathbf{T} + \mathbf{A} = \mathbf{R} \cdot e^{-\beta \cdot \mathbf{z}} + \mathbf{A}_\infty \cdot \left(1 - e^{-\beta \cdot \mathbf{z}}\right) \\ \mathbf{I} \cdot \mathbf{P} = \mathbf{T} \cdot \mathbf{P}_T + \mathbf{A} \cdot \mathbf{P}_A \end{cases}$$

$$\text{(a) } \mathbf{T} = \frac{\mathbf{P} \cdot \mathbf{I} - \mathbf{I} \cdot \mathbf{P}_A}{\mathbf{P}_T - \mathbf{P}_A} \qquad \text{(b) } \mathbf{R} = \frac{\mathbf{T} \cdot \mathbf{A}_\infty}{\mathbf{A}_\infty - (\mathbf{I} - \mathbf{T})}$$

Eq. (7) of the paper

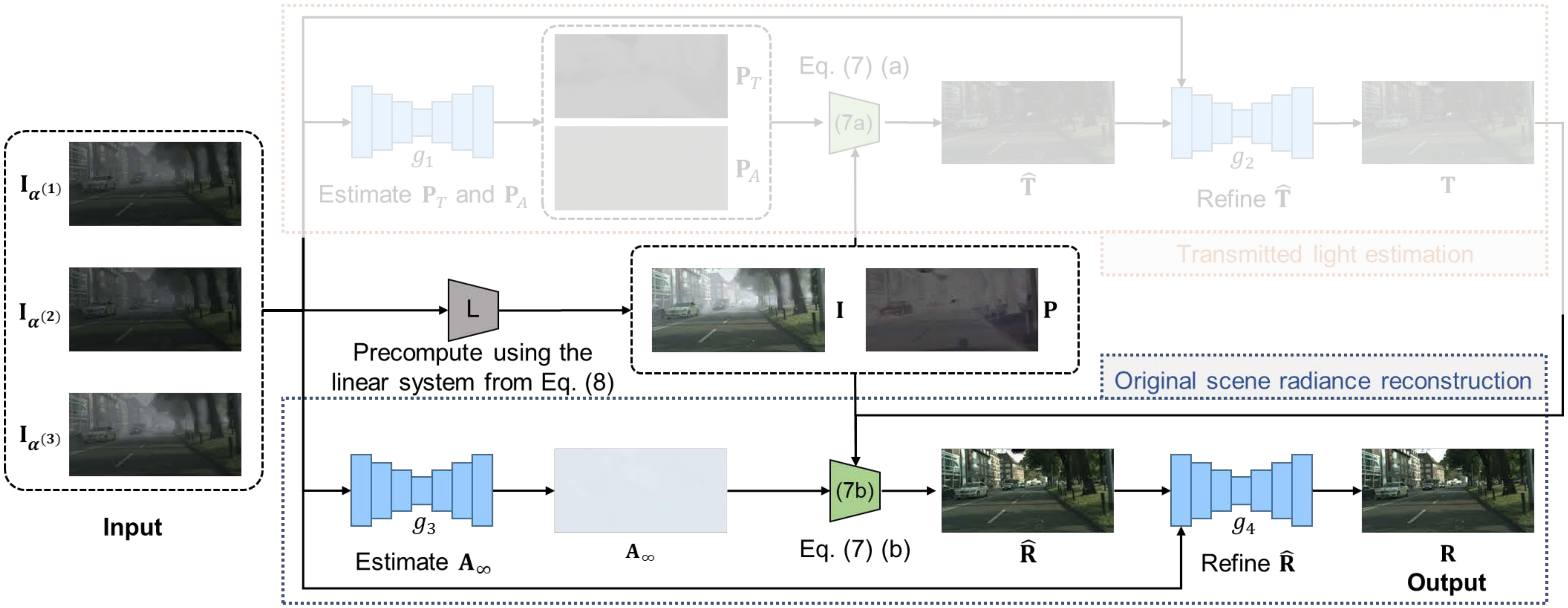
Network: stage 1



The first stage is for transmitted light estimation:

$$\mathbf{T} = \frac{\mathbf{P} \cdot \mathbf{I} - \mathbf{I} \cdot \mathbf{P}_A}{\mathbf{P}_T - \mathbf{P}_A}$$

Network: stage 2



The second stage is for original scene radiance reconstruction: $\mathbf{R} = \dfrac{\mathbf{T} \cdot \mathbf{A}_\infty}{\mathbf{A}_\infty - (\mathbf{I} - \mathbf{T})}$

Results on synthetic data

	Ours	SPCVE [54]	GDN [44]	BPP [82]	FFA [65]	HardGAN [5]	MSBDN [7]
PSNR	**28.32**	15.94	26.54	24.93	26.84	26.22	26.94
MS-SSIM	**0.951**	0.521	0.928	0.915	0.934	0.928	0.932

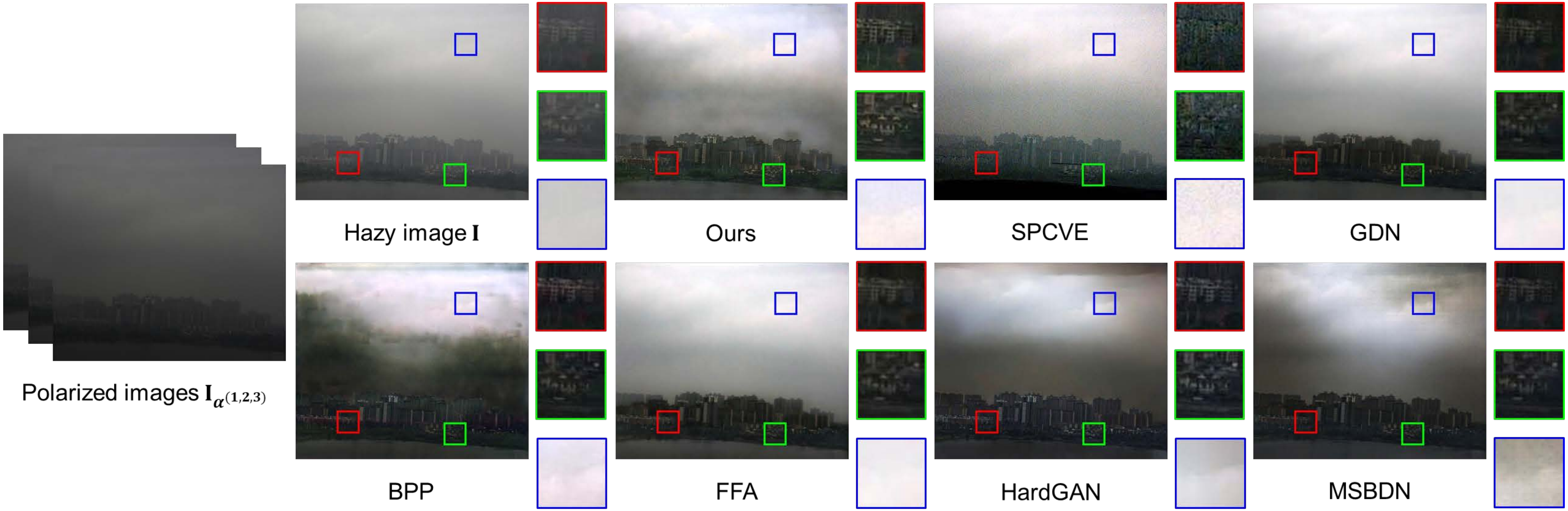
- **A state-of-the-art polarization-based dehazing methods:**
    - **SPCVE:** Skyless polarimetric calibration and visibility enhancement. Optics Express, 2009.
- **Five learning-based single-image dehazing methods:**
    - **GDN:** GridDehazeNet: Attention-based multi-scale network for image dehazing. In Proc. of ICCV, 2019.
    - **BPP:** Single image dehazing for a variety of haze scenarios using back projected pyramid network. In Proc. of ECCVW, 2020.
    - **FFA:** FFA-Net: Feature fusion attention network for single image dehazing. In Proc. of AAAI, 2020.
    - **HardGAN:** HardGAN: A haze-aware representation distillation GAN for single image dehazing. In Proc. of ECCV, 2020.
    - **MSBDN:** Multi-scale boosted dehazing network with dense feature fusion. In Proc. of CVPR, 2020.

Results on synthetic data: visualization (part1)

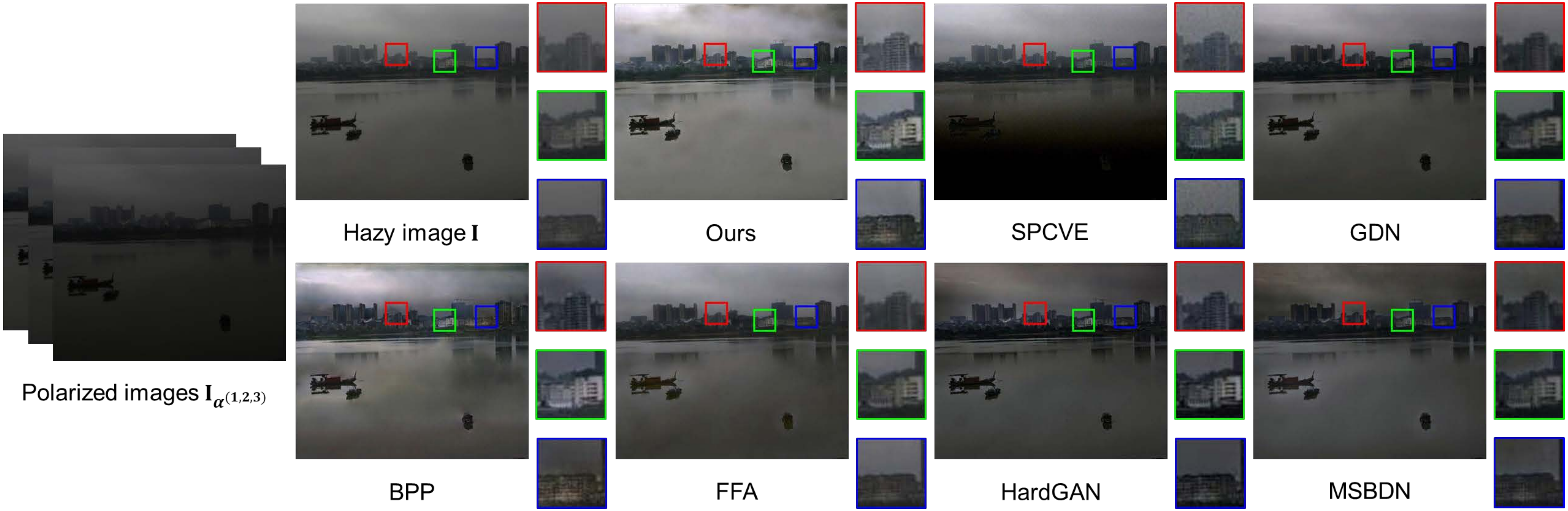
Results on synthetic data: visualization (part2)

Results on synthetic data: visualization (part3)

Results on real data: visualization (part1)



Results on real data: visualization (part2)



Conclusion

- A generalized physical formation model of hazy images
  - taking into account the polarization effects of both transmitted light and airlight
  - along with the spatially-variant real-world scattering
- A robust polarization-based dehazing pipeline
  - without the requirement of specific clues
  - by adopting deep learning to estimate necessary physical parameters
- A two-stage neural network
  - making full use of semantic and contextual information to handle the spatially-variant real-world scattering

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