Supplementary Material: Quality-Improved and Property-Preserved Polarimetric Imaging via Complementarily Fusing

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A.   More information about the Stokes parameters

When placing a polarizer with polarizer angle α in front of the camera, according to the Malus' law [3], the captured polarized image[1] $\mathbf{I}_\alpha$ can be calculated as

$$\mathbf{I}_\alpha = \frac{1}{2}\mathbf{I} \cdot (1 - \mathbf{p} \cdot \cos(2(\alpha - \boldsymbol{\theta}))), \tag{1}$$

where $\mathbf{I}$ denotes the total intensity of the light, which can be regarded as the unpolarized image (*i.e.*, the image captured without using the polarizer), $\mathbf{p} \in [0, 1]$ and $\boldsymbol{\theta} \in [0, \pi]$ denote the degree of polarization (DoP) and the angle of polarization (AoP) of the incoming light to the sensor respectively. Reformulating Eq. (1) into a polynomial form, $\mathbf{I}_\alpha$ can be expressed as a linear combination of three parameters $\mathbf{S}_{0,1,2}$:

$$\mathbf{I}_\alpha = \frac{1}{2}\mathbf{S}_0 - \frac{1}{2}\cos(2\alpha) \cdot \mathbf{S}_1 - \frac{1}{2}\sin(2\alpha) \cdot \mathbf{S}_2, \tag{2}$$

$$\text{where} \quad \begin{cases} \mathbf{S}_0 = \mathbf{I} \\ \mathbf{S}_1 = \mathbf{I} \cdot \mathbf{p} \cdot \cos(2\boldsymbol{\theta}) \\ \mathbf{S}_2 = \mathbf{I} \cdot \mathbf{p} \cdot \sin(2\boldsymbol{\theta}) \end{cases} \tag{3}$$

are called the Stokes parameters [4] of the incoming light to the sensor. Once $\mathbf{S}_{0,1,2}$ are available, the DoP $\mathbf{p}$ and AoP $\boldsymbol{\theta}$ could be acquired by

$$\mathbf{p} = \frac{\sqrt{\mathbf{S}_1^2 + \mathbf{S}_2^2}}{\mathbf{S}_0} \quad \text{and} \quad \boldsymbol{\theta} = \frac{1}{2}\arctan(\frac{\mathbf{S}_2}{\mathbf{S}_1}). \tag{4}$$

The downstream polarization-based vision applications (*e.g.*, reflection removal [5], shape from polarization [2], dehazing [9], *etc.*) usually require the DoP $\mathbf{p}$ and AoP $\boldsymbol{\theta}$ to provide physical clues. To acquire $\mathbf{p}$ and $\boldsymbol{\theta}$, we need at least three polarized images with different polarizer angles since Eq. (3) contains three unknowns $\mathbf{S}_{0,1,2}$. In practice, instead of using a conventional camera equipped with a polarizer to capture three times by rotating the polarizer, using a polarization camera could be more convenient. This is because a polarization camera (*e.g.*, the Lucid Vision Phoenix polarization

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[1]Here we assume the camera response function to be linear since the polarization cameras usually output images with a linear camera response function. Besides, we only focus on linear polarization (*i.e.*, do not consider circular polarization) since polarization cameras only equip linear polarizers.

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camera used in this work) can capture a polarized snapshot $\mathcal{I}$ consisting of four polarized images $\mathbf{I}_{\alpha_{1,2,3,4}}$ with different polarizer angles $\alpha_{1,2,3,4} = 0°, 45°, 90°, 135°$ in a single shot. Plugging $\alpha_{1,2,3,4}$ into Eq. (1), Eq. (2), and Eq. (3), we could deduce that the Stokes parameters $\mathbf{S}_{0,1,2}$ can be directly calculated from $\mathbf{I}_{\alpha_{1,2,3,4}}$:

$$\begin{cases} \mathbf{S}_0 = \frac{1}{2}(\mathbf{I}_{\alpha_1} + \mathbf{I}_{\alpha_2} + \mathbf{I}_{\alpha_3} + \mathbf{I}_{\alpha_4}) = \mathbf{I}_{\alpha_1} + \mathbf{I}_{\alpha_3} = \mathbf{I}_{\alpha_2} + \mathbf{I}_{\alpha_4} \\ \mathbf{S}_1 = \mathbf{I}_{\alpha_3} - \mathbf{I}_{\alpha_1} \\ \mathbf{S}_2 = \mathbf{I}_{\alpha_4} - \mathbf{I}_{\alpha_2} \end{cases}, \tag{5}$$

making the acquisition of $\mathbf{p}$ and $\boldsymbol{\theta}$ much more easily.

B. Additional results on synthetic data

In this section, we provide additional visual quality comparisons on synthetic data among our framework, the state-of-the-art polarized image low-light enhancement method PLIE [10] and its improved version PLIE+, the only existing polarized image deblurring method PolDeblur [11] and its improved version PolDeblur+, and four learning-based image enhancement methods designed for conventional images that also fuse noisy and blurry pairs (LSD2 [6], LSFNet [1], SelfIR [7], and D2HNet [8]), as shown in Fig. A., Fig. B., and Fig. C..

C. Additional results on real data

In this section, we provide additional visual quality comparisons on real data among our framework, the state-of-the-art polarized image low-light enhancement method PLIE [10] and its improved version PLIE+, the only existing polarized image deblurring method PolDeblur [11] and its improved version PolDeblur+, and four learning-based image enhancement methods designed for conventional images that also fuse noisy and blurry pairs (LSD2 [6], LSFNet [1], SelfIR [7], and D2HNet [8]), as shown in Fig. D., Fig. E., and Fig. F..

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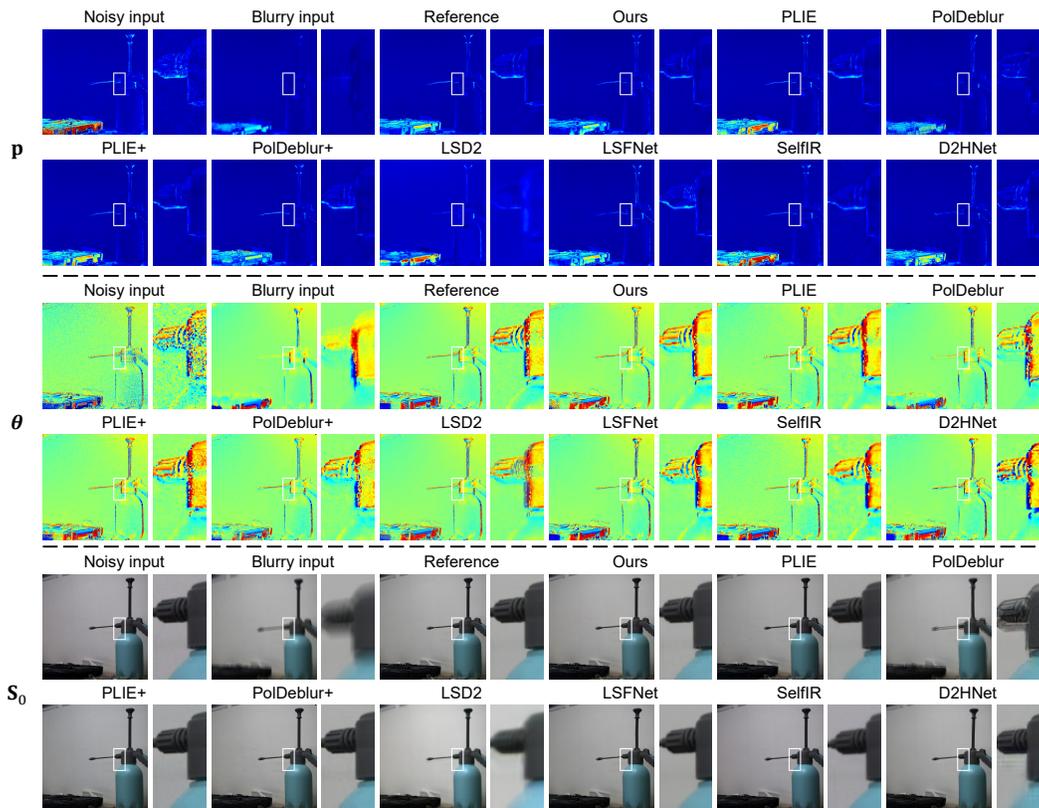
Figure A.: Additional visual quality comparisons on synthetic data (part1).

3
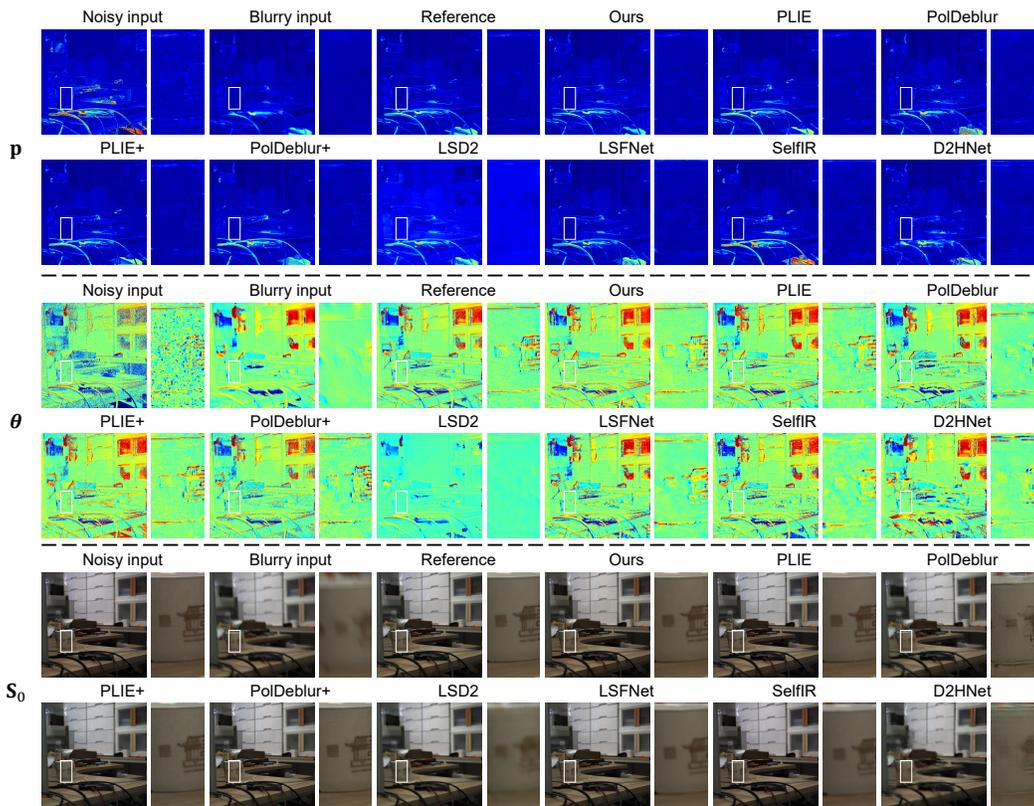
Figure B.: Additional visual quality comparisons on synthetic data (part2).

4
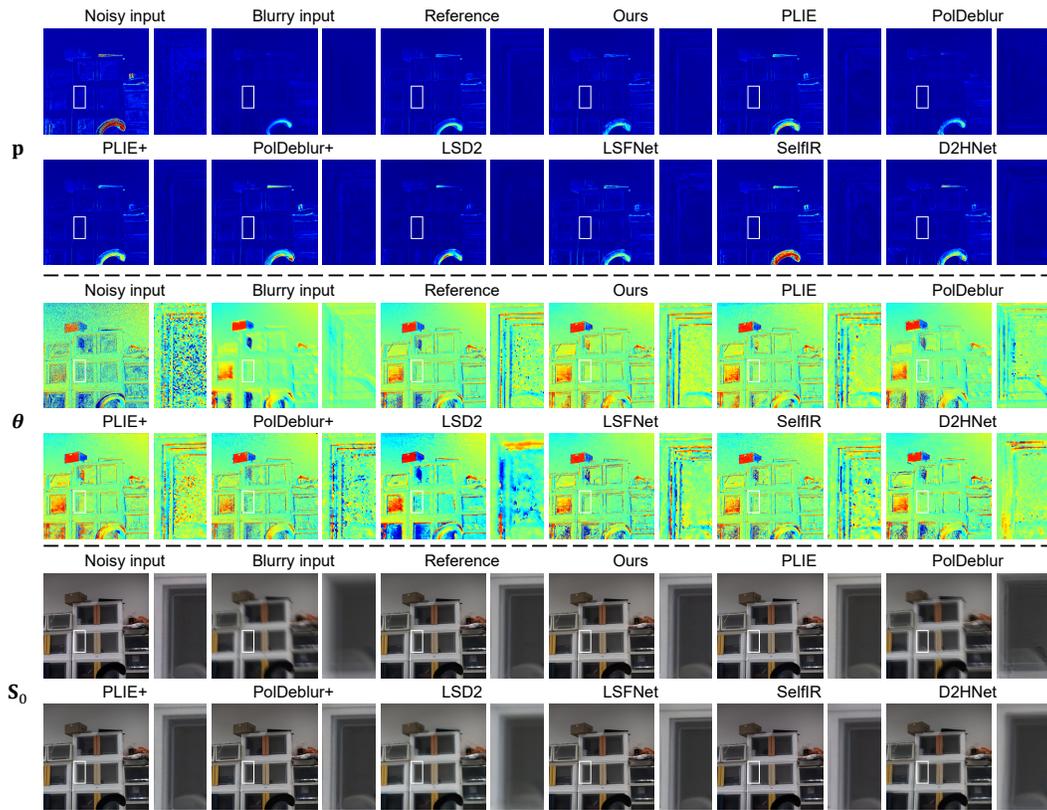
Figure C.: Additional visual quality comparisons on synthetic data (part3).

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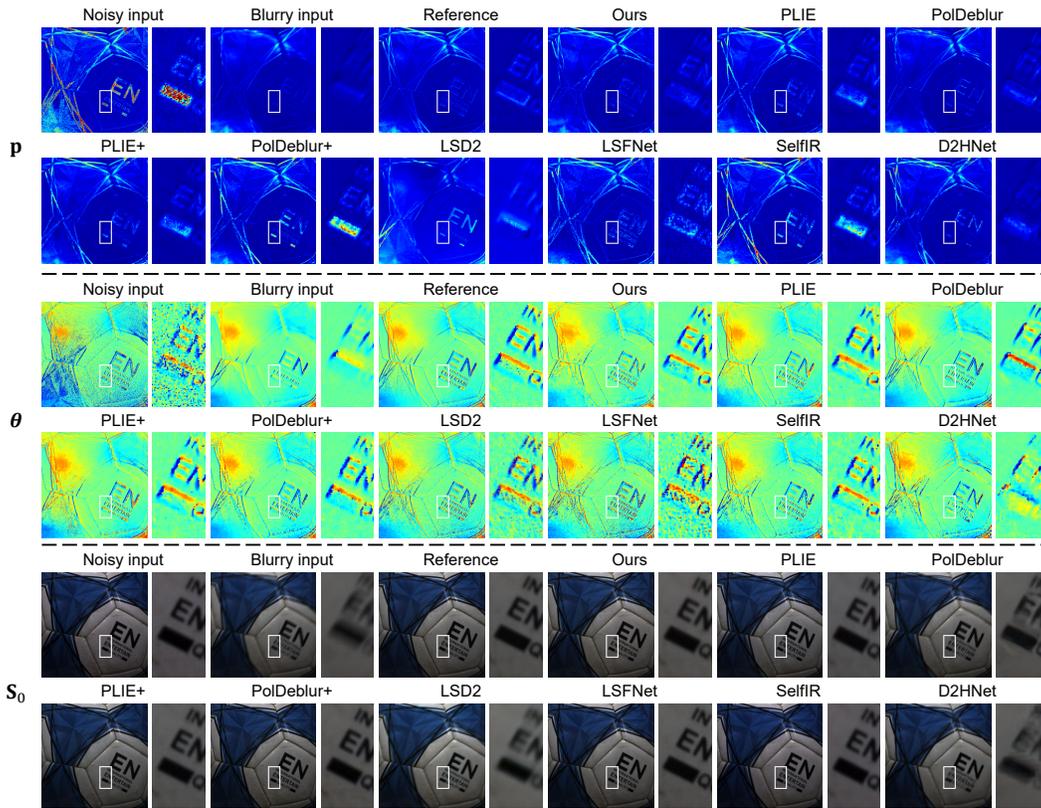
Figure D.: Additional visual quality comparisons on real data (part1).

6
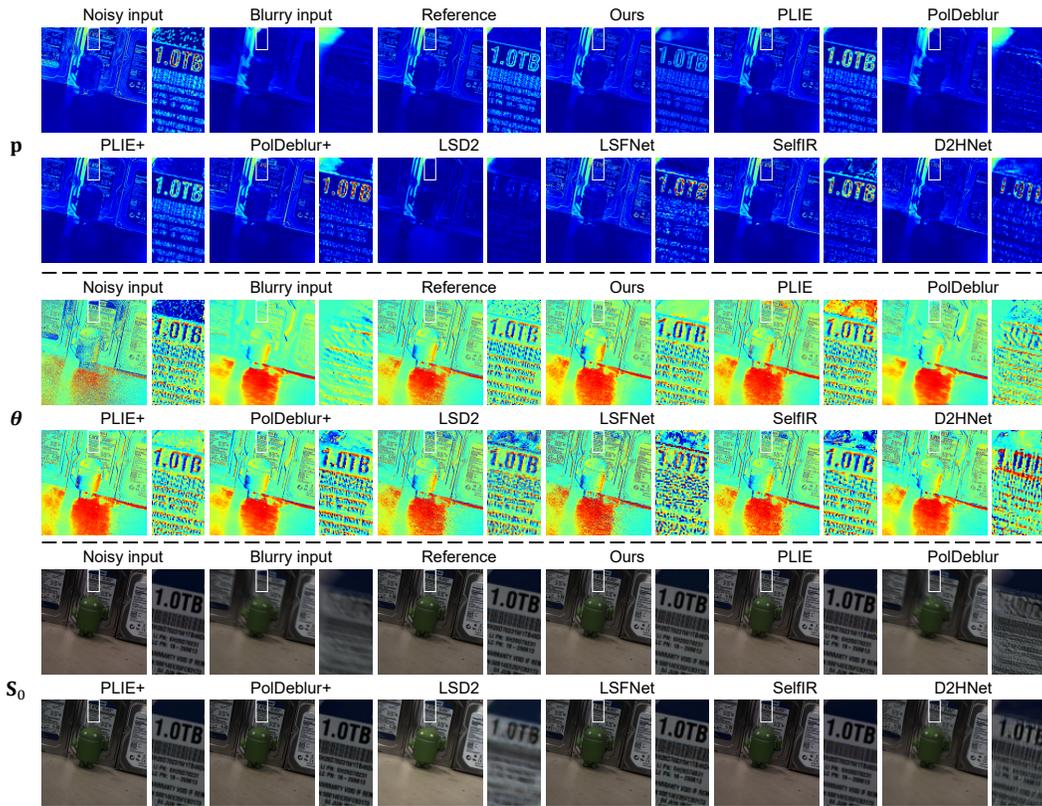
Figure E.: Additional visual quality comparisons on real data (part2).

7
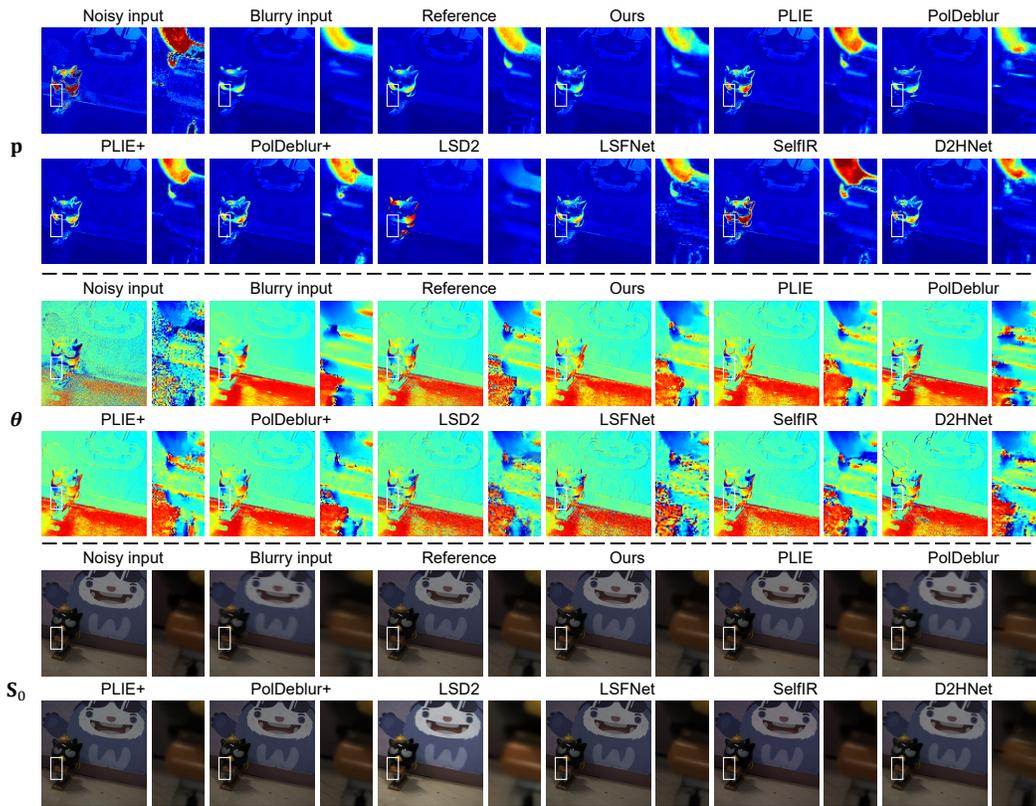
Figure F.: Additional visual quality comparisons on real data (part3).

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