We sincerely thank all reviewers for their valuable comments and suggestions, and feel encouraged that all reviewers like the originality of the proposed capturing setup and image formation model. We will fix the typos and improve visualizations pointed out by reviewers in the final version. The code and dataset will also be released as R1 suggested. Below we respond to specific comments and concerns.

R2: The detail of finetuning ReflectNet [22] and the result of training ReflectNet from scratch. Since ReflectNet needs three images captured with different polarizer angles, we generated two additional polarization images for each pair of (un)polarized images in our dataset, then finetuned ReflectNet using Adam optimizer with a learning rate of 0.005 for 5 epochs. We also trained ReflectNet solely on our datasets with the same training strategy used for our model. The result is shown in Table 1. We can see that its result is similar to that of the finetuned model and worse than ours.

Table 1: Quantitative evaluation results.

		Ours	Ours-Initial	ReflectNet-Finetuned	ReflectNet-Scratch	Ours-Parabola	Ours-2% noise	Ours-8% noise	Ours-16% noise
Transmission	SSIM	**0.9708**	0.8324	0.9627	0.9582	0.8846	0.9691	0.9668	0.9619
	PSNR	**28.23**	21.61	27.52	28.01	24.40	28.08	27.31	27.17
Reflection	SSIM	**0.8953**	0.6253	0.8303	0.8525	0.4833	0.8785	0.8418	0.8022
	PSNR	**20.92**	13.90	18.50	18.48	13.69	20.53	19.18	18.26

R2&R3: Evaluation of the initial separation. The quantitative evaluation of our initial physically-based separation ($\hat{I}_r$ and $\hat{I}_t$) is listed in Table 1, and some qualitative results are shown in Fig. 1 left. We can see that the initial separation is effective, and our refinement network helps eliminate the artifact and noise caused by rough estimation of ξ and ζ.

R2: Comparison with ReflectNet without feeding ξ and ζ. We removed ξ and ζ from the input of our refinement network as suggested, and fed the results of ReflectNet and our initial separation into this refinement network. Under this setup, the SSIM and PSNR are 0.8721(R)&0.9632(T) and 20.02(R)&27.38(T) for our method, and are 0.8084(R)&0.9594(T) and 18.30(R)&27.20(T) for ReflectNet. We can see that even with this refinement ReflectNet still performs worse than our full pipeline. It also shows the importance of feeding ξ and ζ into the refinement network.

R2: Better visualization. We stretched the minimum and maximum intensity values of the results of different algorithms in a consistent range as shown in Fig. 1 right. We can see our results are still clearly better with more detailed structures compared to ReflectNet.

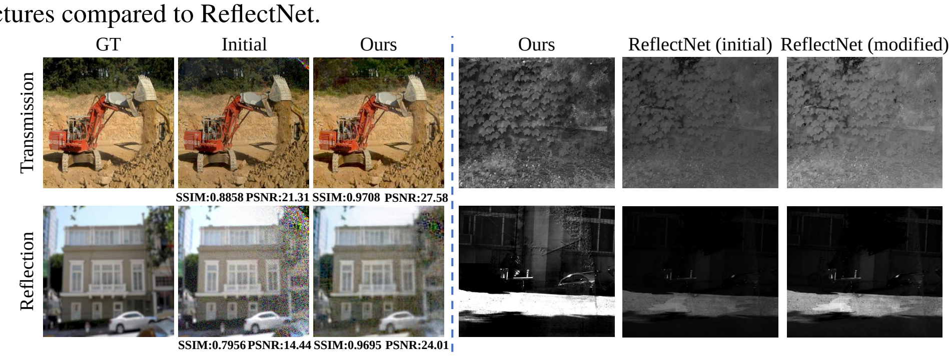

Figure 1: Left: examples of initial physically-based separation and our final output. Right: results of our model and ReflectNet after modifying the dynamic range.

R2: Selection of the polarizer angle. Because $\phi_\perp(x)$ can be an arbitrary value in the range of $[0, 2\pi)$, $\phi - \phi_\perp(x)$ has the same range regardless of the value of ϕ. Moreover, $\cos^2(y)$ and $\sin^2(y)$ are periodic functions with a period of π (Equation (2) in our paper). As a result, our formulation does not rely on the selection of polarizer angle ϕ. As long as the polarization images are captured under the same polarizer angle ϕ during training and testing, our method will work.

R2: Effect of the reflection gradient loss. We find that the different performance of gradient loss on the transmission and reflection is due to the fact that the signal of the reflection is usually much weaker than the transmission in input images. We will consider designing a more effective gradient loss that improves both layers in our future work.

R3: Limitations of the proposed method. Our model assumes the semireflector approximately has a planar shape. When it becomes a curved shape such as windshield in a car, our semireflector orientation estimation module will fail, and thus the performance of our method will deteriorate. We generated the test data using the parabola surface simulation as ReflectNet, and directly tested using our current model. The result is listed in Table 1. We can see that the performance becomes much worse especially for the reflection. The performance might be improved if we modify the semireflector orientation estimation module accordingly, and we will consider this as our future work.

R3: Algorithm analysis on noise sensitivity. In our experiment, we added uniform noise to the polarization angle ϕ when generating the polarization image. We further tested our method against Gaussian noise added to images with different standard deviations. The results are shown in Table 1. We can see that our method performs consistently well and is robust to Gaussian noise.