DeepBasis: Single-Image SVBRDF Estimation via Two-Level Basis Materials Model -Supplemental Material-

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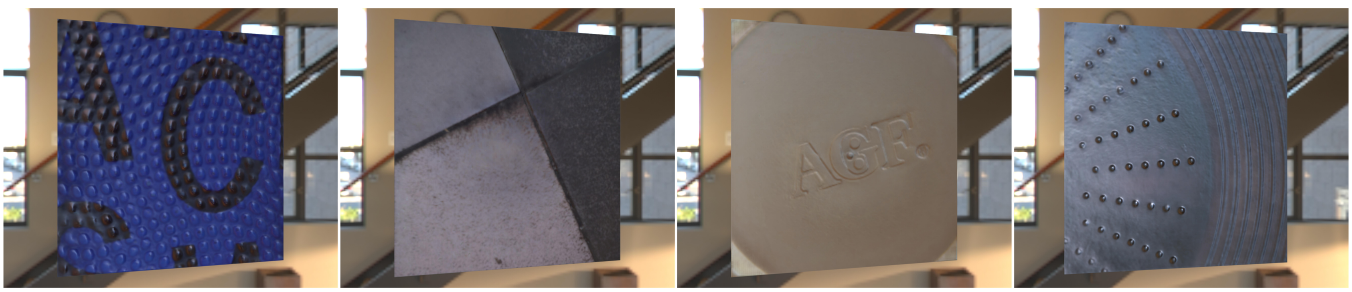

Figure 1: The rendering of our estimated real-world material under the environment lighting.

CCS CONCEPTS

• **Computing methodologies** → **Reflectance modeling**.

KEYWORDS

Material Reflectance Modeling, SVBRDF, Basis Maiterials, Deep Learning, Rendering

ACM Reference Format:

Li Wang, Lianghao Zhang, Fangzhou Gao, and Jiawan Zhang. 2023. DeepBasis: Single-Image SVBRDF Estimation via Two-Level Basis Materials Model -Supplemental Material- . In *SIGGRAPH Asia 2023 Conference Papers (SA Conference Papers '23), December 12–15, 2023, Sydney, NSW, Australia.* ACM, New York, NY, USA, 8 pages. https://doi.org/10.1145/3610548.3618239

1 EXPOSITION OF BASIS REFINEMENT

The previous refinement strategy proposed by [Gao et al. 2019] minimize the disparity between the input images I and the rendered images. Its optimization variables consist of per-pixel reflectance maps M:

$$\arg\min_{M} ||R(M, l) - I|| \tag{1}$$

where $R(\cdot)$ is the rendering operation and l is the lighting directions. Different from the previous strategy, the jointly prediction of basis materials and blending weights allow us to build the optimization variables on bases. Furthermore, the utilization of two-level basis material model enables the individual optimization on the global bases:

$$\arg\min_{B^g} ||R(L(B^g + B^l, W), l) - I|| \tag{2}$$

where $L(\cdot)$ is the linear combination operation, W is the blending weights, B^g is the global bases and B^l is the local bases. The predicted weights are fixed during optimization, and they hold the spatial information of material sample. Therefore, the adjustment of bases according to the local deviation between input image and rendered image can correspondingly adjust the full material reflecatnce maps. It can effectively avoid the local overfitting caused by single-image optimization.

We conduct a comparative analysis between the previous refinement strategy and our basis refinement approach, as shown in Figure 2. In this experiment, the initial SVBRDF is estimated by our DeepBasis. With the exception of the optimization variables, all other optimization options remain unchanged. The results demonstrate that the direct refinement method leads to localized overfitting in the highlight regions of the input image, resulting in artifacts present in both the reflectance maps and the re-rendered

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SA Conference Papers '23, December 12–15, 2023, Sydney, NSW, Australia

ACM ISBN 979-8-4007-0315-7/23/12…$15.00
https://doi.org/10.1145/3610548.3618239

images, as highlighted in the red box. In contrast, our basis refinement can effectively avoid overfitting, and even slightly address overfitting as shown in blue box. Furthermore, it can fine-tune the predicted SVBRDF to closely match the input sample, such as the overall color calibration of the specular map in the Figure 2.

Therefore, our basis refinement approach, as compared to direct reflectance map refinement, exhibits superior robustness. It provides stable improvements to the estimated SVBRDF, ensuring a higher quality of the re-rendered images.

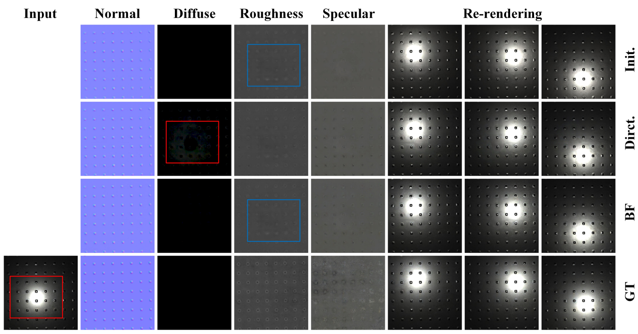

Figure 2: The comparison between per-pixel reflectance maps refinement (Direct.) and basis refinement (BF). And their initialization is the prediction of our DeepBasis (Init.).

2 COMPARISON RESULTS ON SYNTHETIC SCENES

In Figure (3-6), we show more comparison results on synthetic scenes gathered from [Deschaintre et al. 2018, 2019]. Note that for the optimization-based methods [Gao et al. 2019; Guo et al. 2020; Zhou and Kalantari 2022], we offer the additional ground-truth lighting directions. As seen, compared with other previous methods [Deschaintre et al. 2018; Gao et al. 2019; Guo et al. 2020; Zhou and Kalantari 2021, 2022], our method can produce higher quality SVBRDF estimations and re-rendering results.

3 COMPARISON RESULTS ON REAL-WORLD SCENES

Here, we show more comparison results on real-world scenes. The examples in Figure 6 are gathered from [Guo et al. 2020]. Examples from [Zhou and Kalantari 2022] are shown in Figure 7, and our captured examples are shown in Figure 8. Note that, For the methods required lighting directions [Gao et al. 2019; Guo et al. 2020; Zhou and Kalantari 2022], we provide additional calibrate lighting direction obtained from a checkerboard.

ACKNOWLEDGMENTS

This work was supported in part by National Key Research and Development Program of China (2022YFF0904301).

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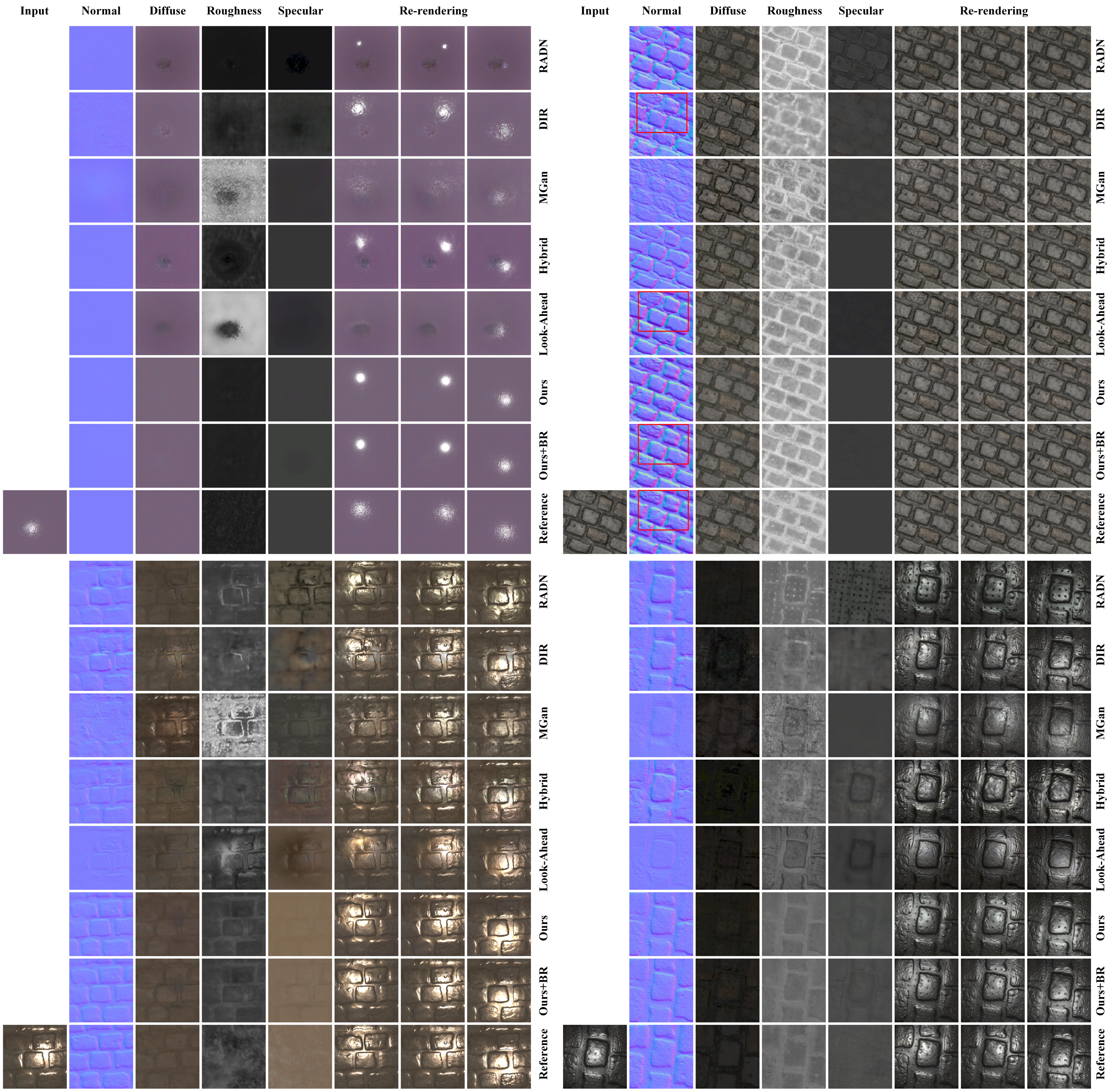

Figure 3: The comparison results on synthetic scenes against single-image SVBRDF estimation methods, RAND of [Deschaintre et al. 2018], Hybrid of [Zhou and Kalantari 2021] and Look-Ahead of [Zhou and Kalantari 2022], and optimization-based methods DIR of [Gao et al. 2019] and MGan of [Guo et al. 2020].

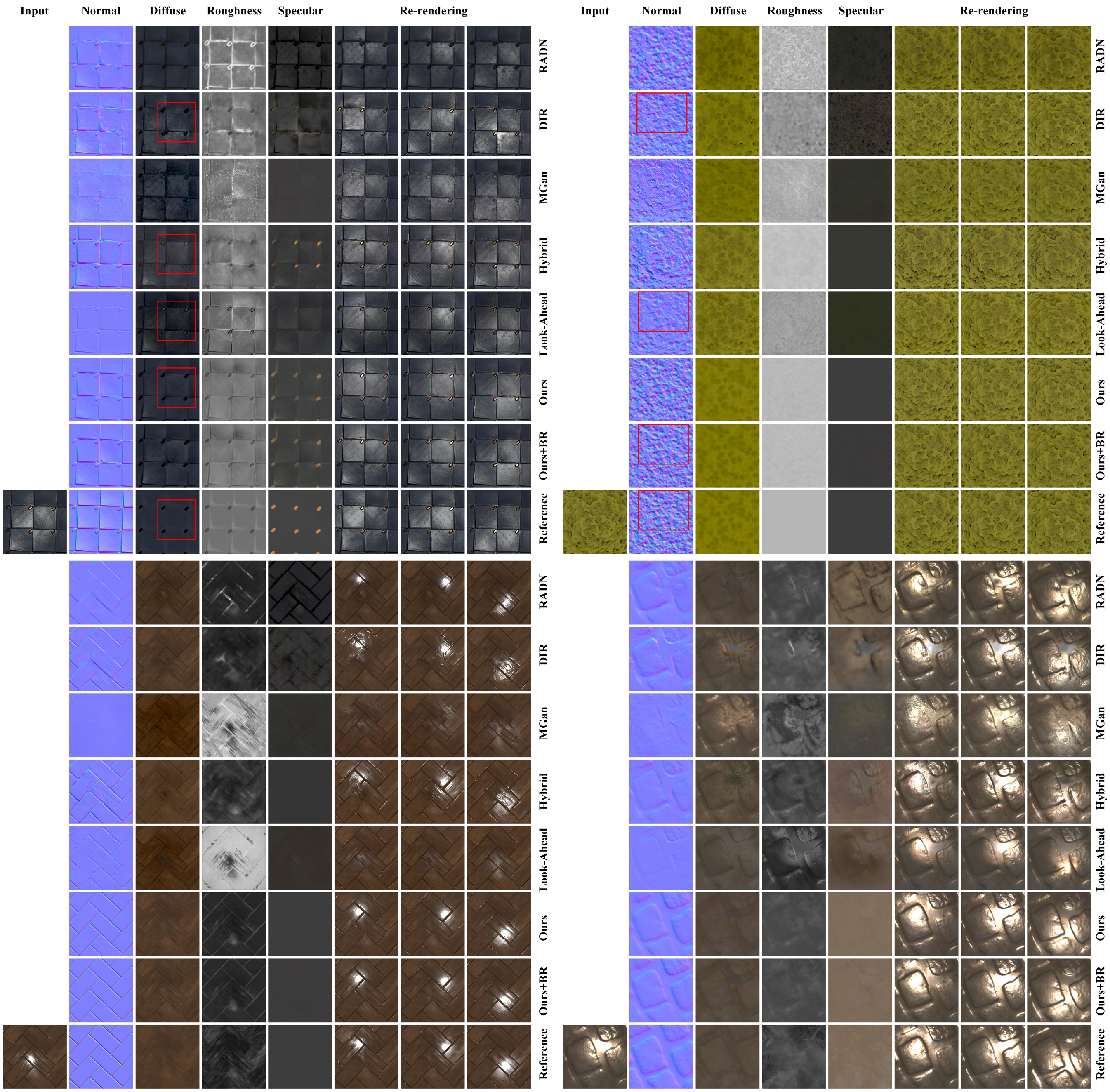

Figure 4: The comparison results on synthetic scenes against single-image SVBRDF estimation methods, RAND of [Deschaintre et al. 2018], Hybrid of [Zhou and Kalantari 2021] and Look-Ahead of [Zhou and Kalantari 2022], and optimization-based methods DIR of [Gao et al. 2019] and MGan of [Guo et al. 2020].

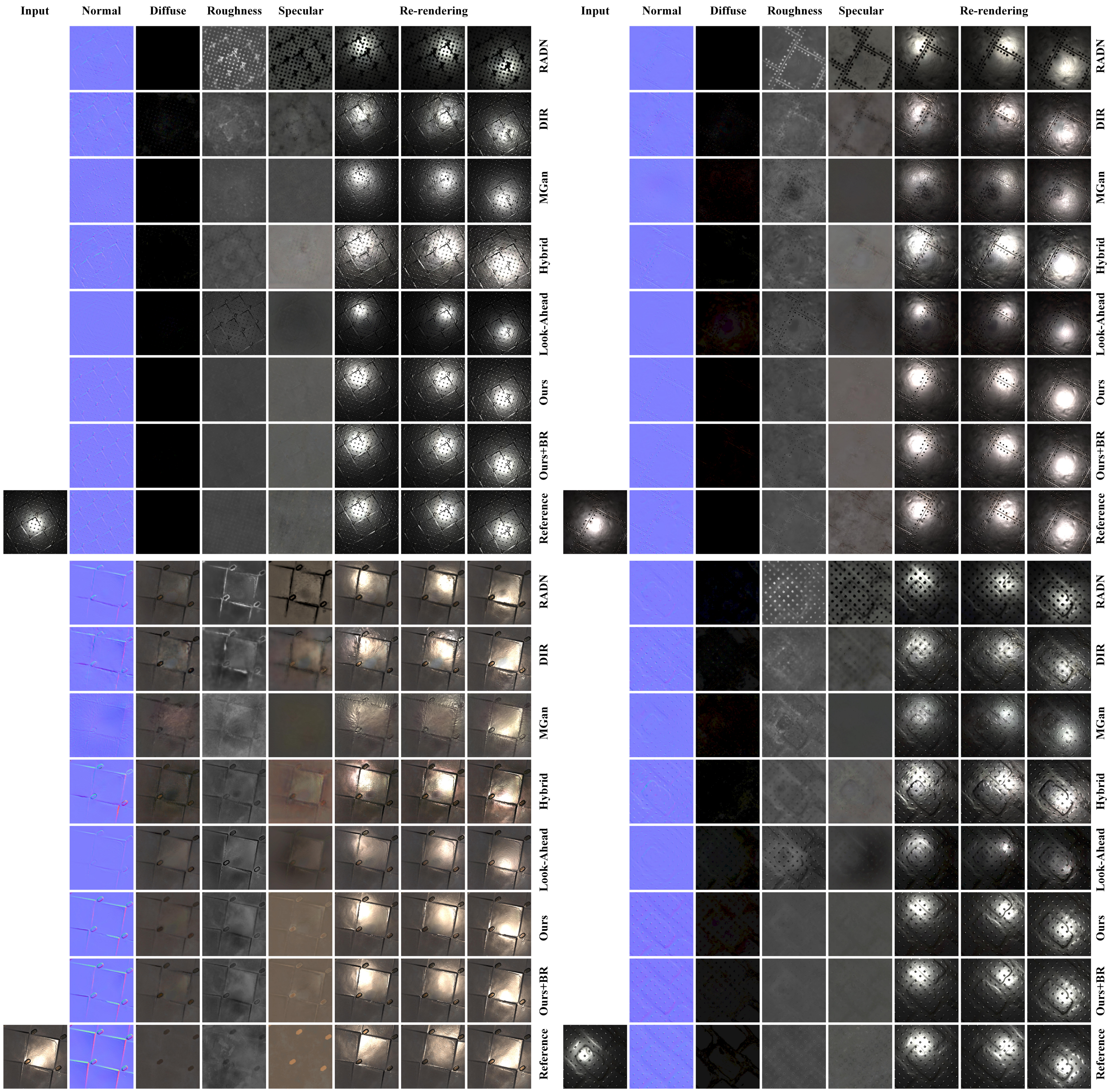

Figure 5: The comparison results on synthetic scenes against single-image SVBRDF estimation methods, RAND of [Deschaintre et al. 2018], Hybrid of [Zhou and Kalantari 2021] and Look-Ahead of [Zhou and Kalantari 2022], and optimization-based methods DIR of [Gao et al. 2019] and MGan of [Guo et al. 2020].

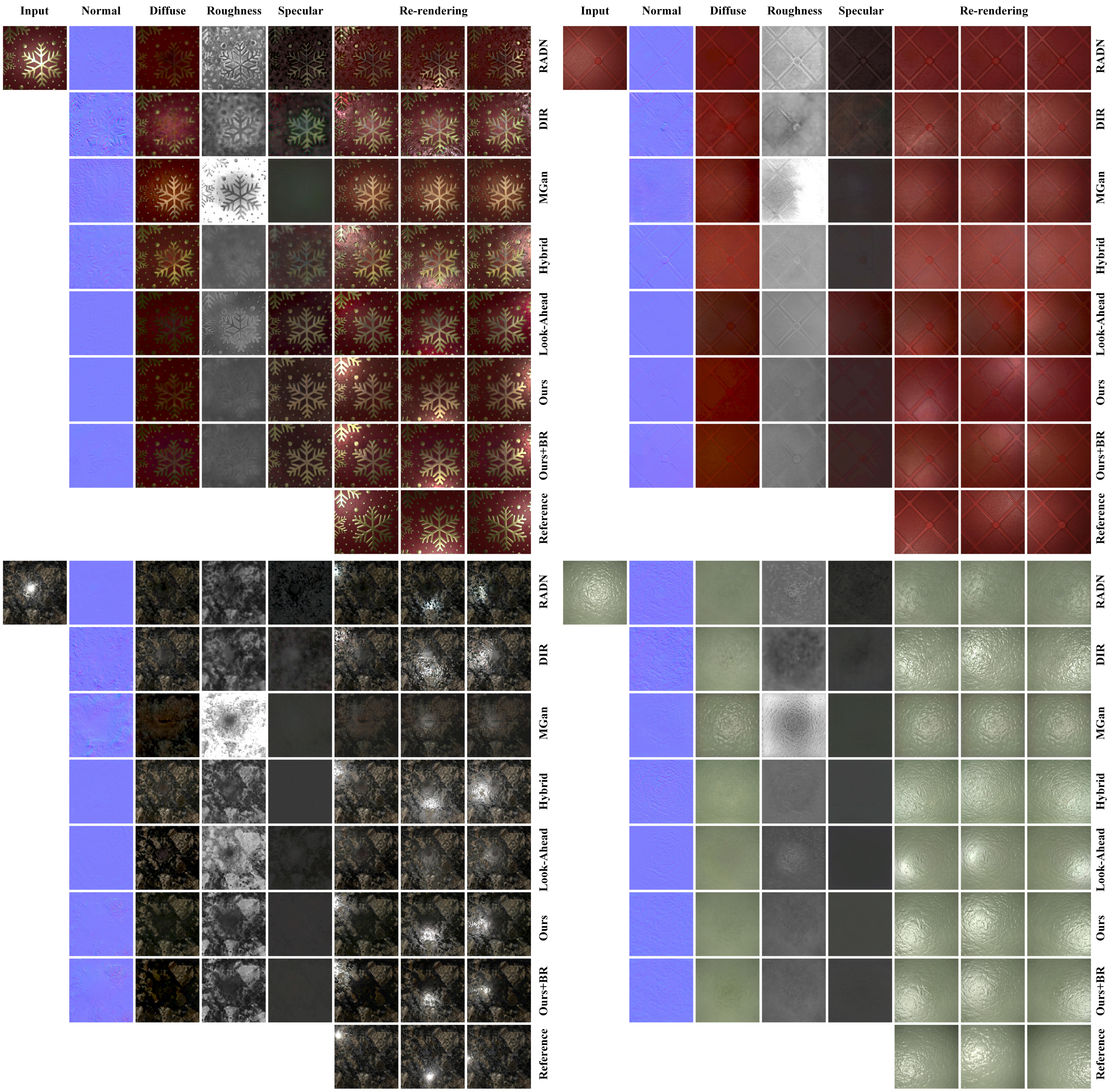

Figure 6: The comparison results on real scenes against single-image SVBRDF estimation methods, RAND of [Deschaintre et al. 2018], Hybrid of [Zhou and Kalantari 2021] and Look-Ahead of [Zhou and Kalantari 2022], and optimization-based methods DIR of [Gao et al. 2019] and MGan of [Guo et al. 2020].

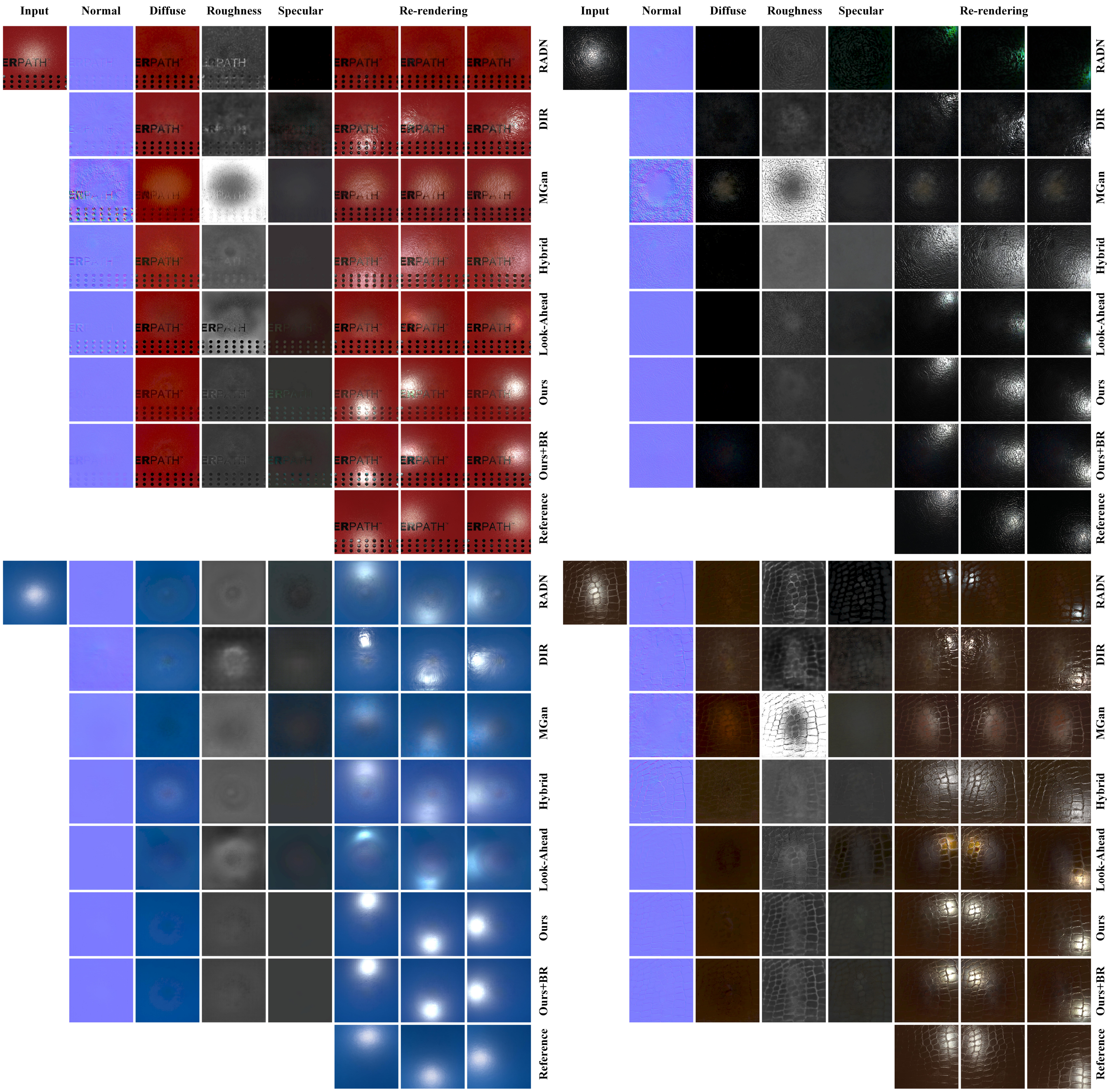

Figure 7: The comparison results on real scenes against single-image SVBRDF estimation methods, RAND of [Deschaintre et al. 2018], Hybrid of [Zhou and Kalantari 2021] and Look-Ahead of [Zhou and Kalantari 2022], and optimization-based methods DIR of [Gao et al. 2019] and MGan of [Guo et al. 2020].

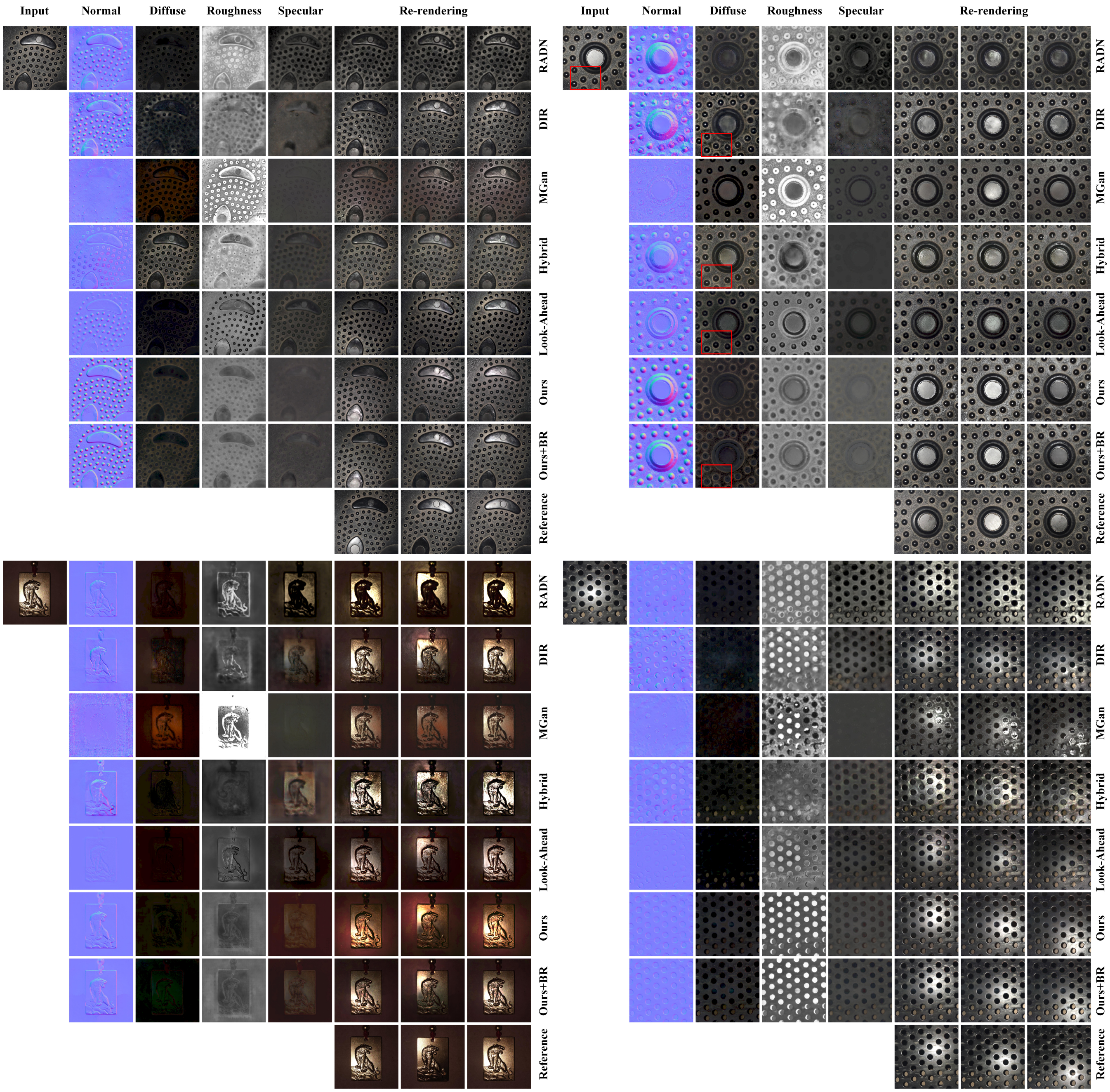

Figure 8: The comparison results on real scenes against single-image SVBRDF estimation methods, RAND of [Deschaintre et al. 2018], Hybrid of [Zhou and Kalantari 2021] and Look-Ahead of [Zhou and Kalantari 2022], and optimization-based methods DIR of [Gao et al. 2019] and MGan of [Guo et al. 2020].