Deep SVBRDF Estimation from Single Image under Learned Planar Lighting

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ABSTRACT

CCS CONCEPTS

• **Computer systems organization → Embedded systems**; *Redundancy*; Robotics; • **Networks** → Network reliability.

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1 DETAILS OF COMPARISON WITH MA ET AL.

Since Ma et al. [2021] use a similar capture device to ours and the code is publicly available, we compare with their method given a single image on synthetic data. When rendering the input measurements of their network, the camera and the planar light source are positioned nearly above the virtual planar sample to capture more specular responses. The planar sample is placed at the center of their valid volume. Besides, we feed the ground-truth shading normal (normal map) to the network to simplify the problem, and then average their predicted roughness α_x/α_y to obtain the final isotropic alpha. The input images of Ma et al. [2021] are scaled to a suitable rendering scale for display, and HDR rendering results are used as inputs when evaluating their the network.

2 ADDITIONAL RESULTS ON REAL-WORLD MATERIALS

In Fig. 1-6, we show the additional predict SVBRDFs of our method from single real photograph. Note that all input images are cropped automatically according to the proposed field of view range.

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3 ADDITIONAL RESULTS ON SYNTHETIC MATERIALS

In Fig 10-18, we also show additional comparison results on synthetic datasets provided by Deschaintre et al. [Deschaintre et al. 2018, 2019]. These materials are not involved in the training process.

REFERENCES

Valentin Deschaintre, Miika Aittala, Fredo Durand, George Drettakis, and Adrien Bousseau. 2018. Single-Image SVBRDF Capture with a Rendering-Aware Deep Network. *ACM Transactions on Graphics* 37, 4CD (2018), 128.1–128.15.

Valentin Deschaintre, Miika Aittala, Fredo Durand, George Drettakis, and Adrien Bousseau. 2019. Flexible SVBRDF Capture with a Multi-Image Deep Network. *Computer Graphics Forum* 38, 4 (2019).

X. Ma, K. Kang, R. Zhu, H. Wu, and K. Zhou. 2021. Free-form scanning of non-planar appearance with neural trace photography. *ACM Transactions on Graphics (TOG)* (2021).

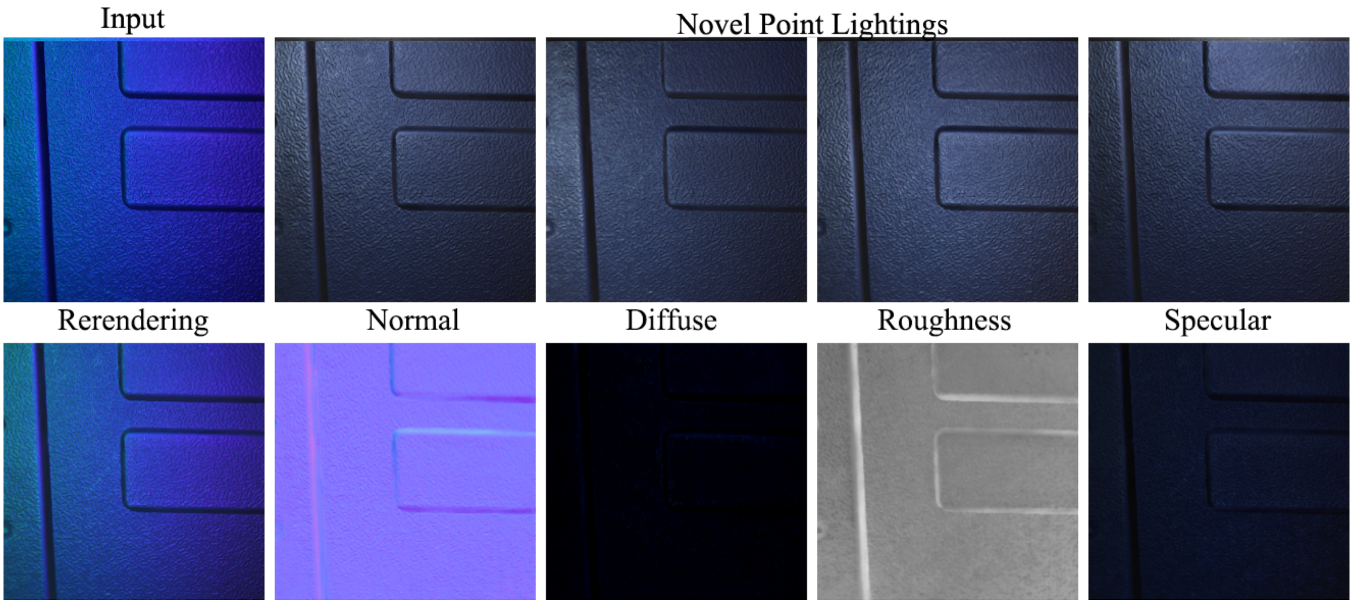

Figure 1: Estimated SVBRDF and rerenderings of a real-world material.

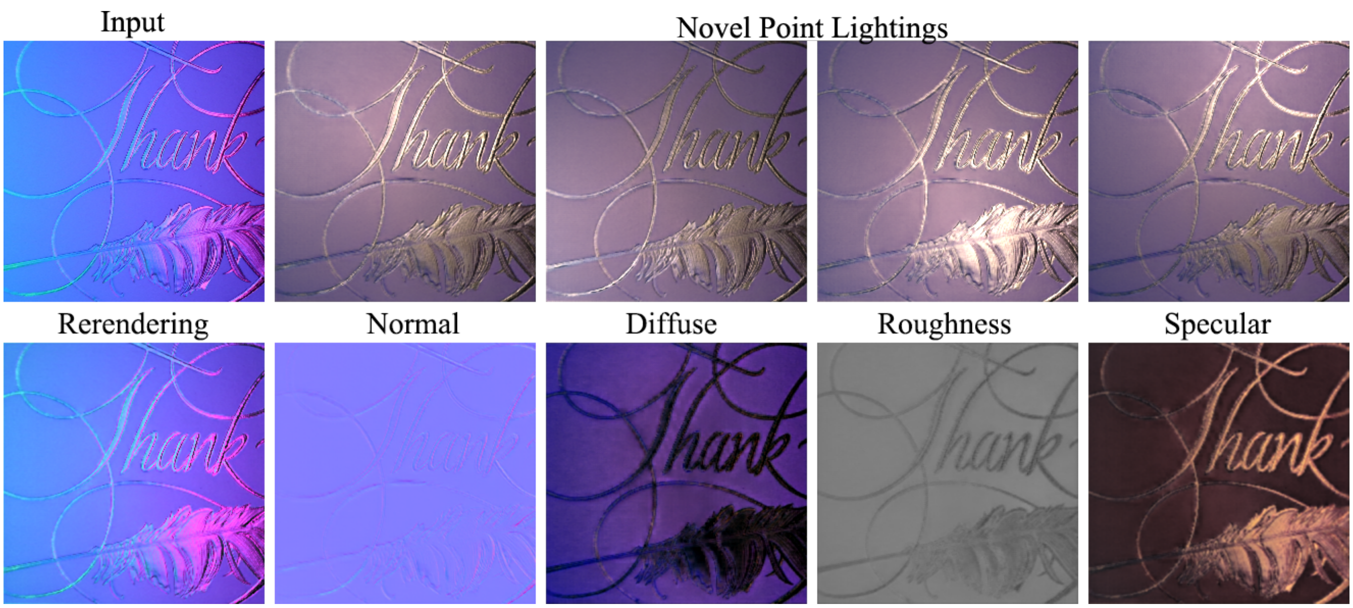

Figure 2: Estimated SVBRDF and rerenderings of a real-world material.

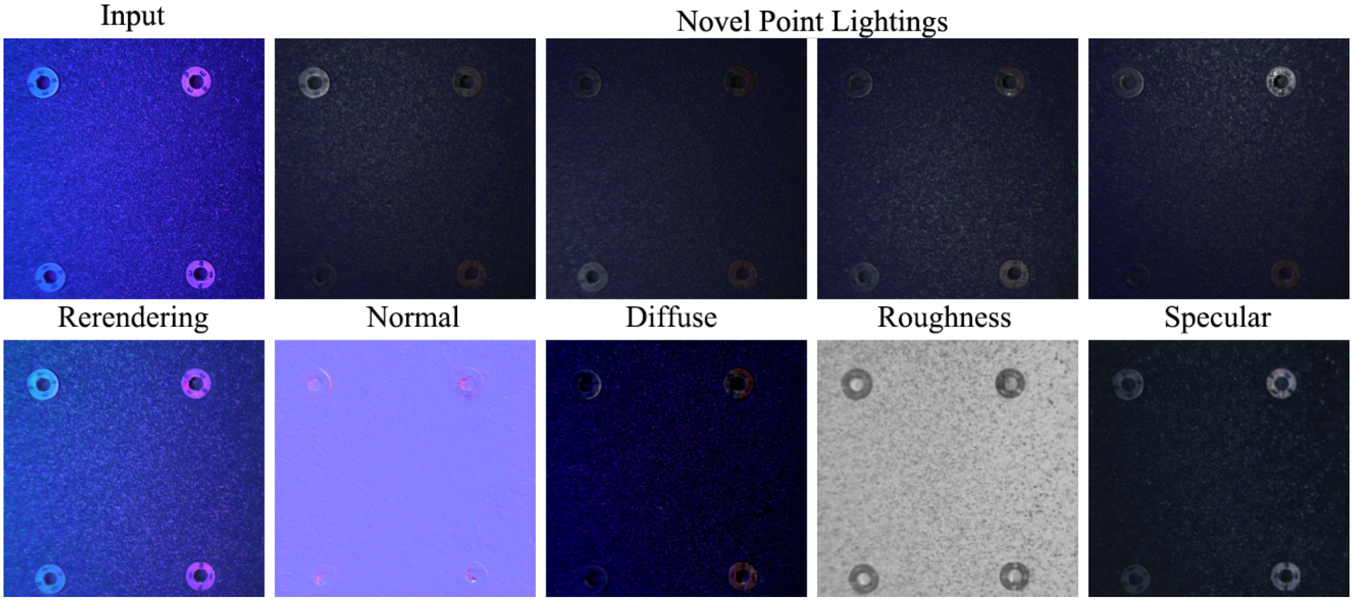

Figure 3: Estimated SVBRDF and rerenderings of a real-world material.

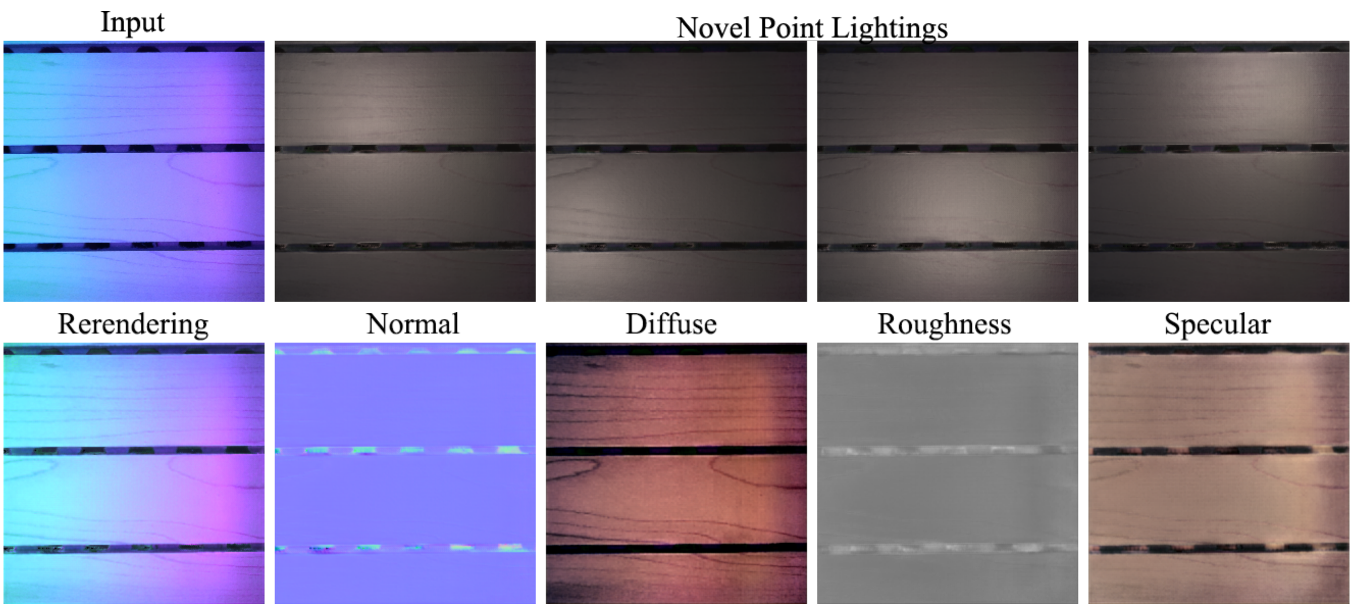

Figure 4: Estimated SVBRDF and rerenderings of a real-world material.

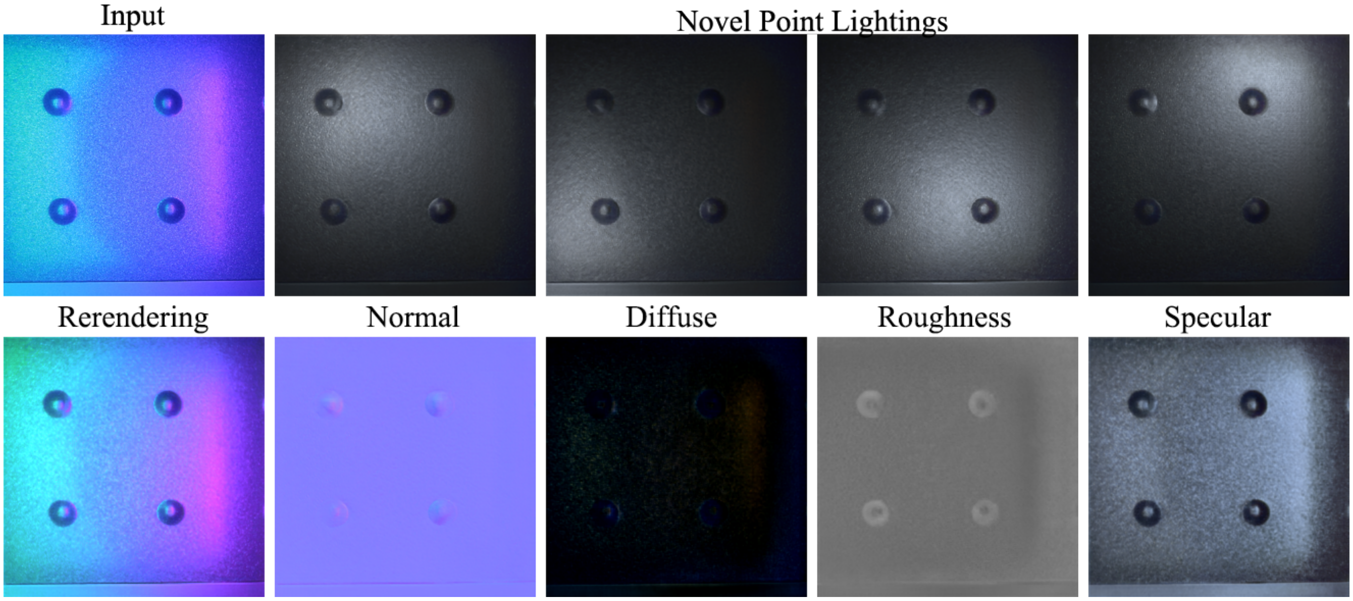

Figure 5: Estimated SVBRDF and rerenderings of a real-world material.

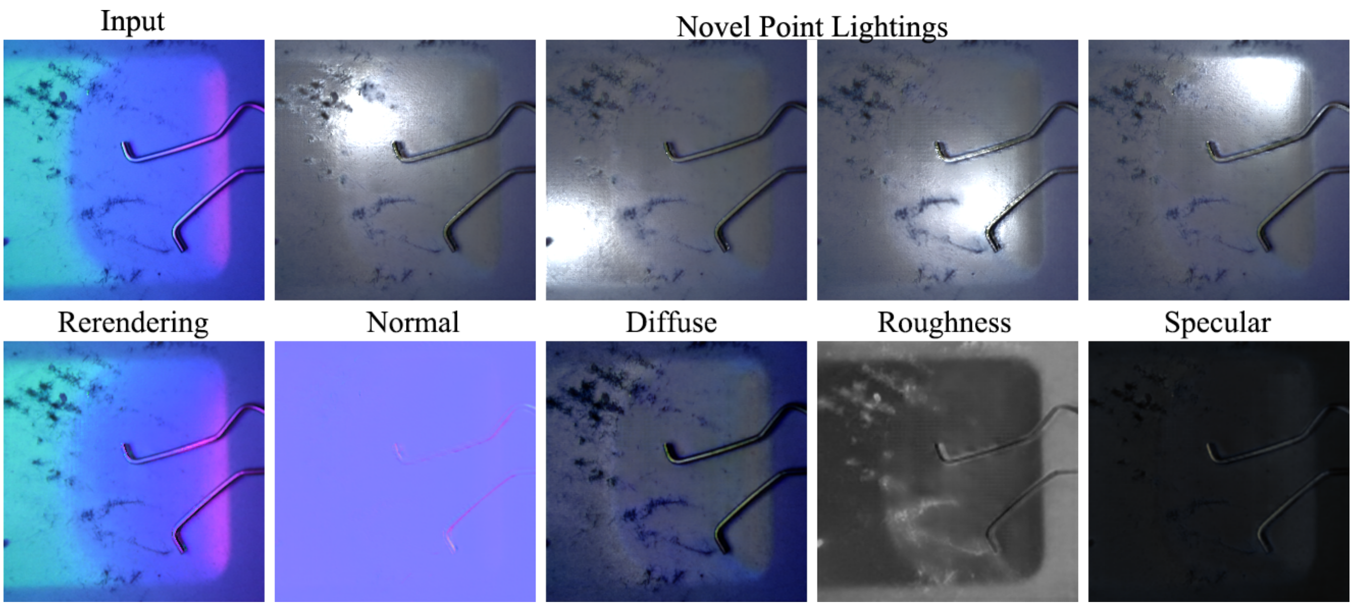

Figure 6: Estimated SVBRDF and rerenderings of a real-world material. This is a mirror-like material mentioned in the limitation. Although the lighting is baked in albedo maps, the normal and roughness are accurate in the area captured in mirror directions. As seen in Fig 7, our method can reconstruct the mirror-like material on synthetic dataset. This suggests that our method can potentially handle this type of materials with carefully calibrations.

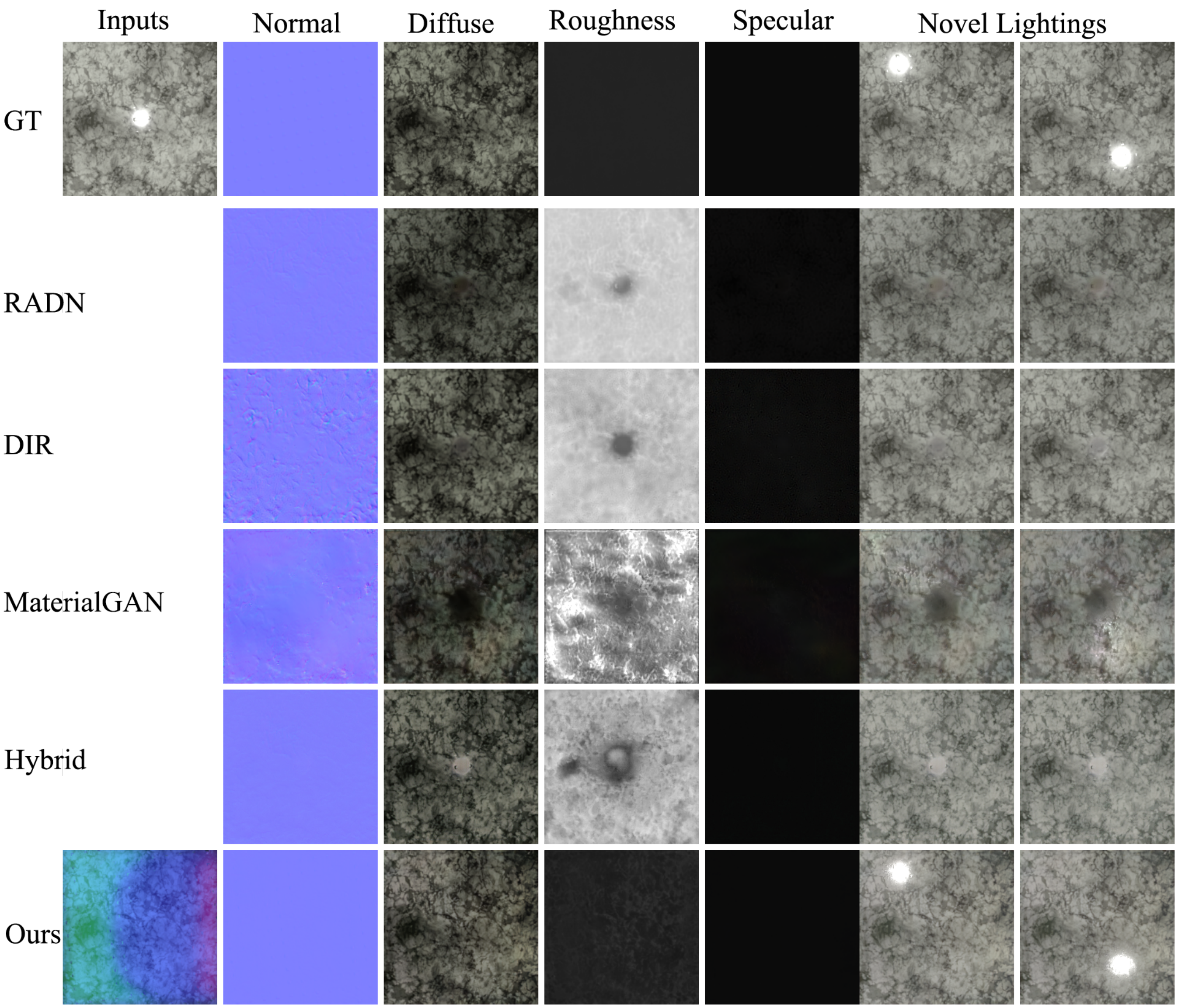

Figure 7: Comparison against RADN, DIR, MaterialGAN and Hybrid on a mirror-like material.

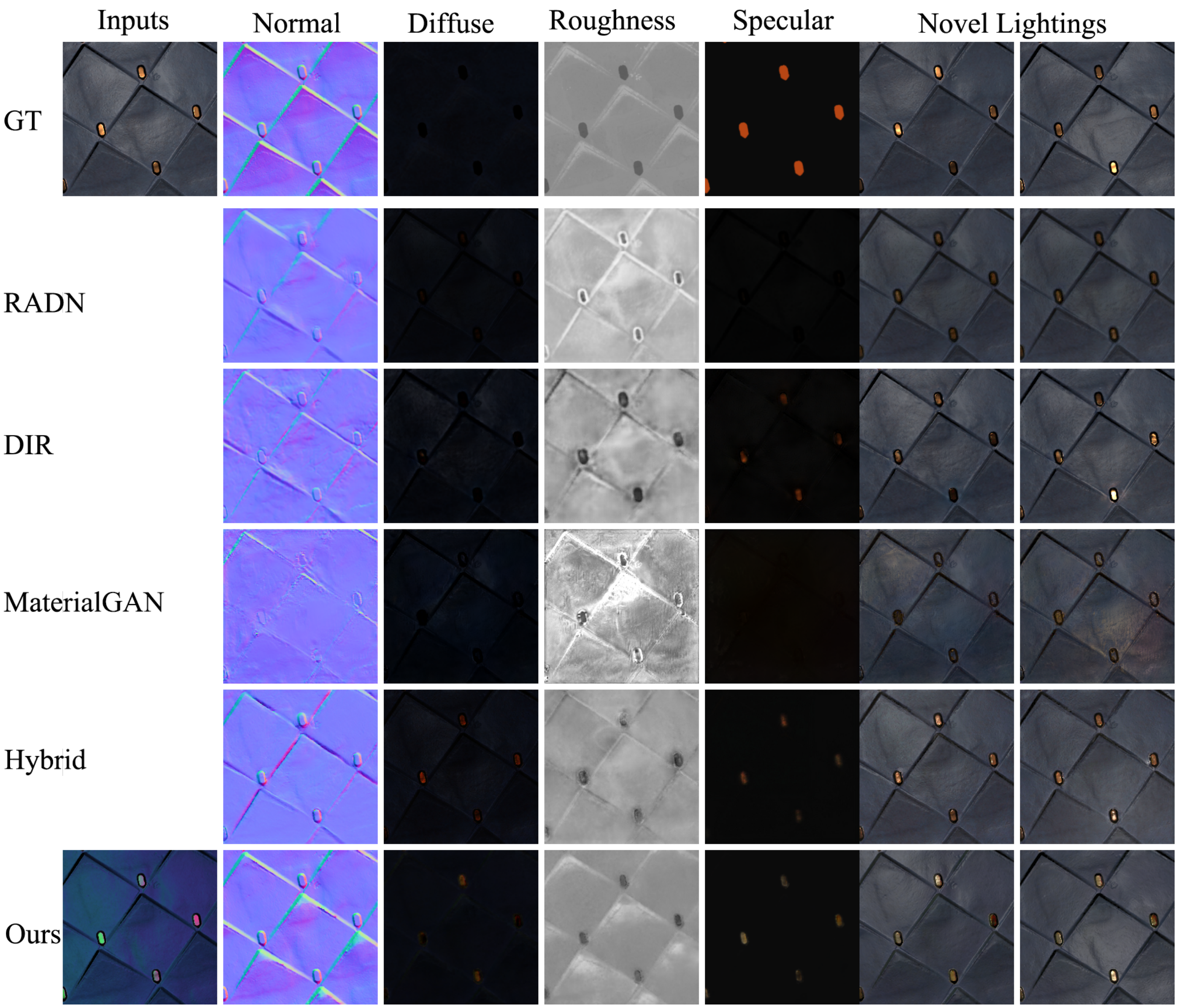

Figure 8: Comparison against RADN, DIR, MaterialGAN and Hybrid on a mirror-like material.

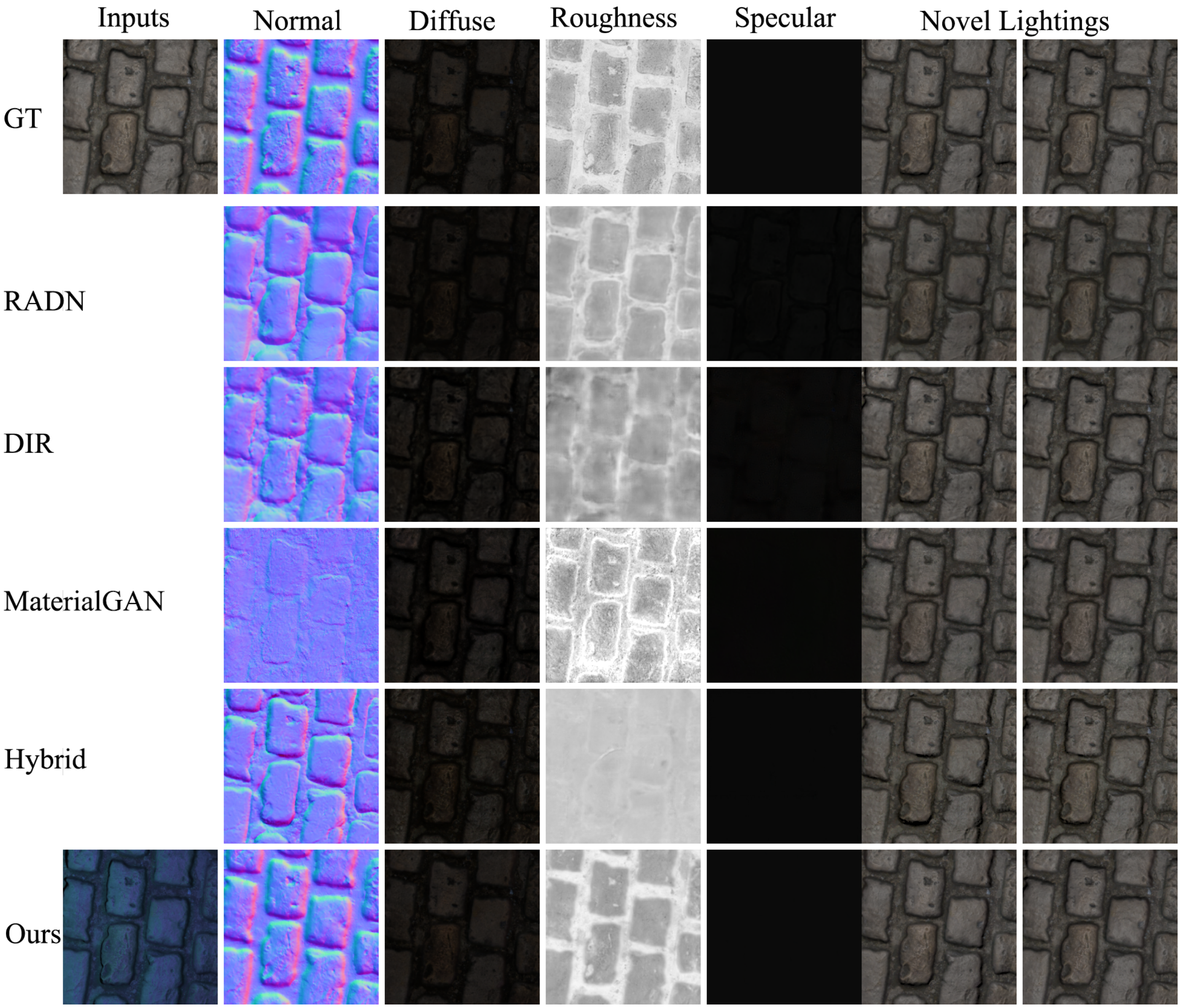

Figure 9: Comparison against RADN, DIR, MaterialGAN and Hybrid on a mirror-like material.

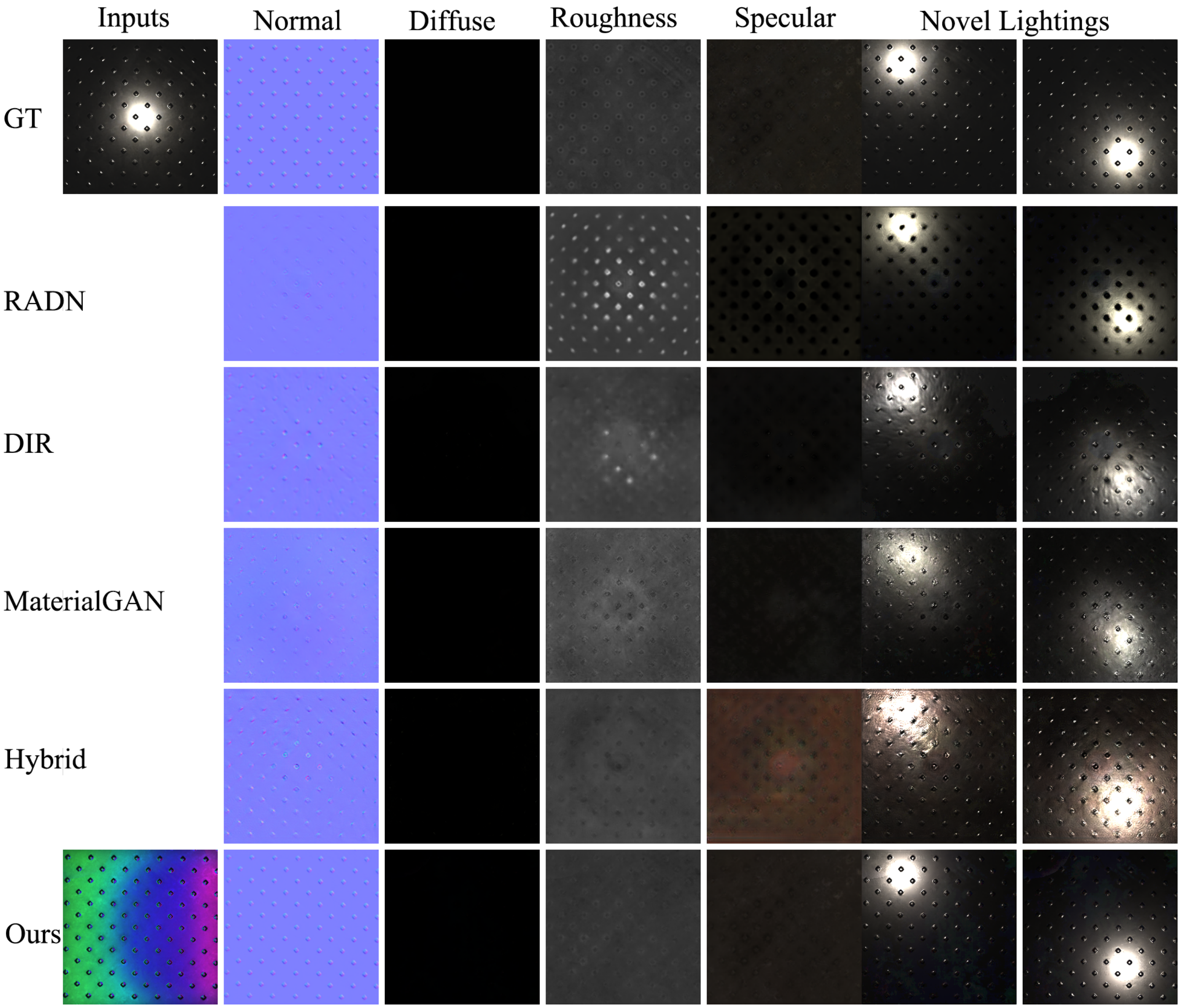

Figure 10: Comparison against RADN, DIR, MaterialGAN and Hybrid on synthetic material.

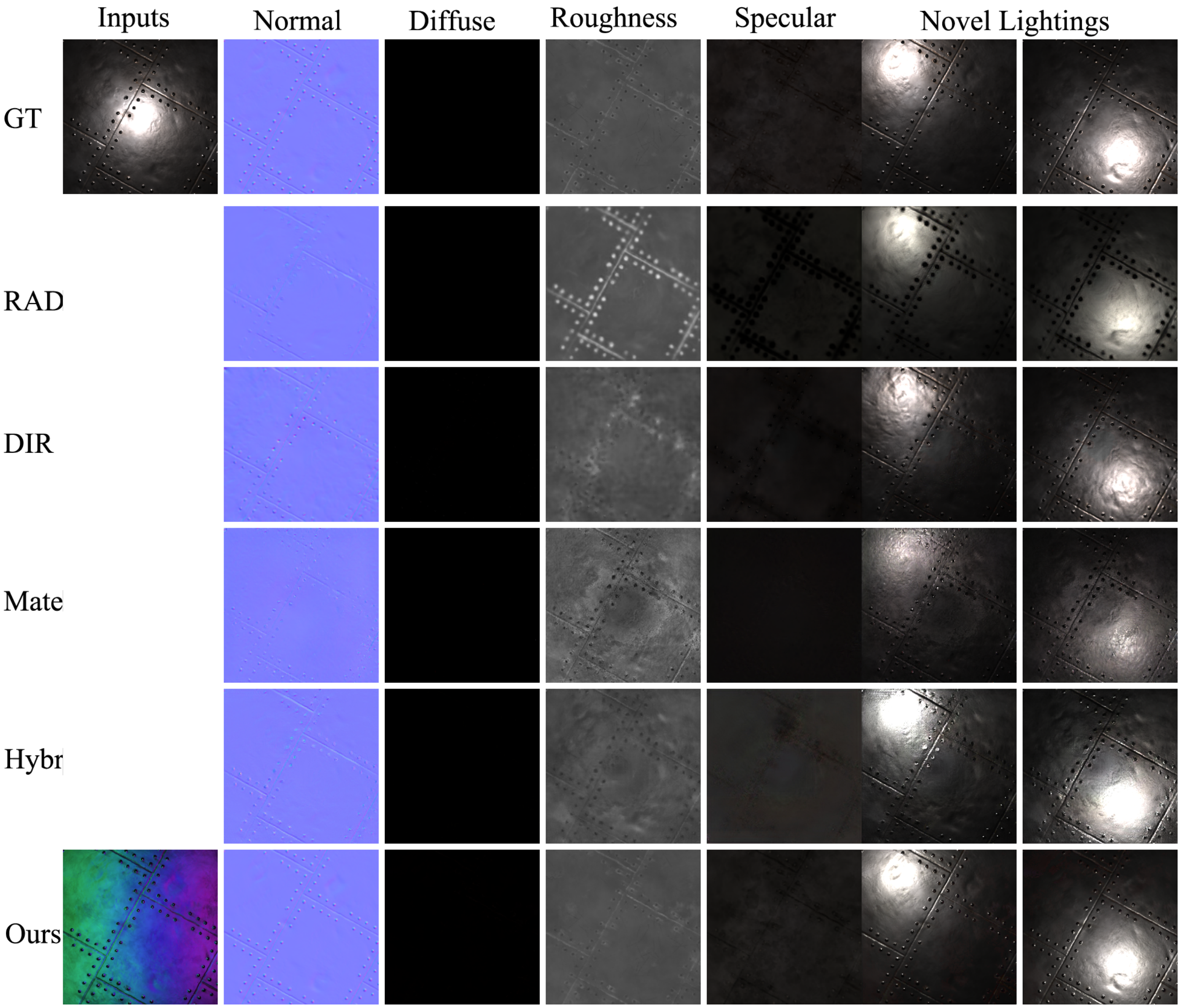

Figure 11: Comparison against RADN, DIR, MaterialGAN and Hybrid on synthetic material.

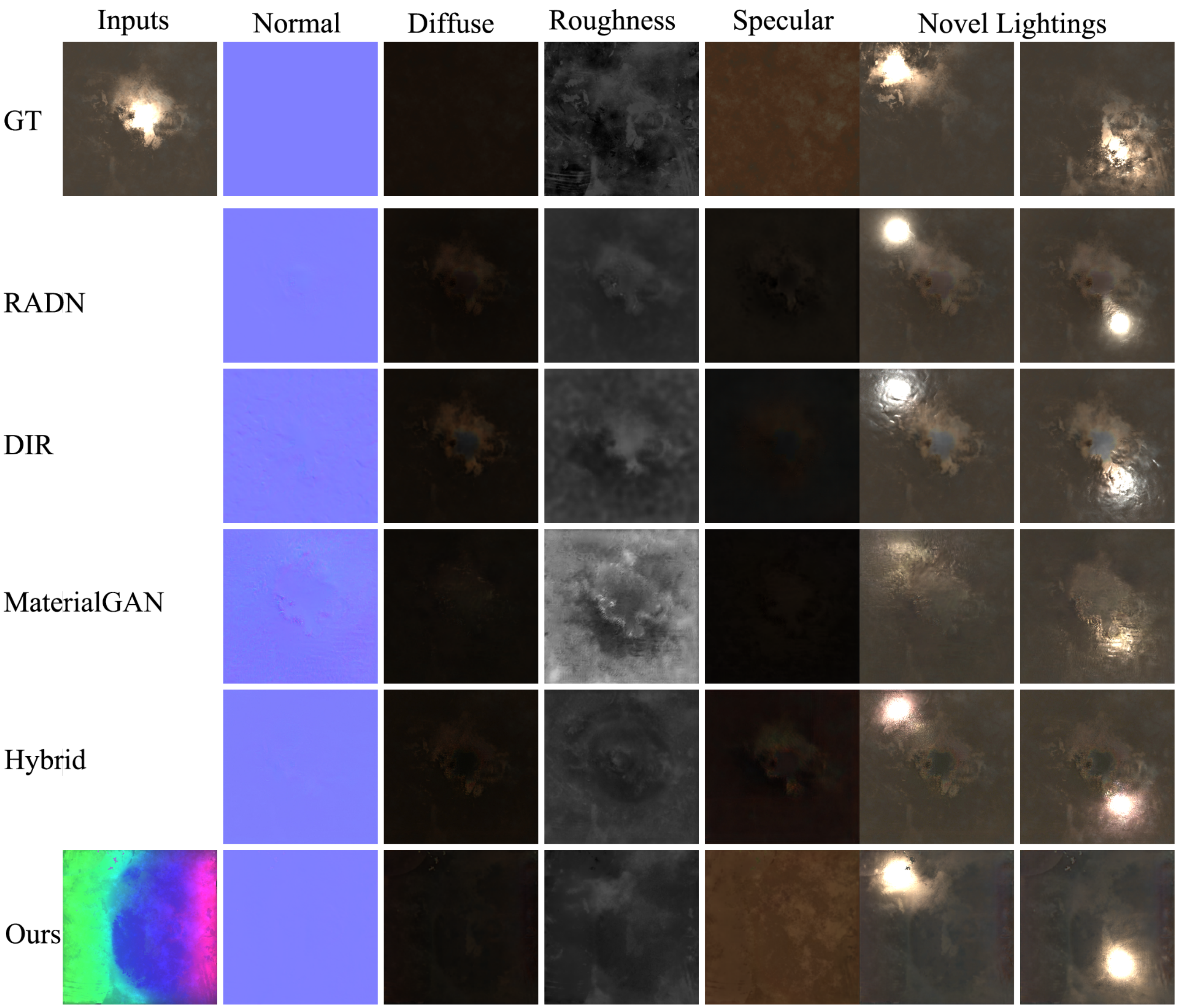

Figure 12: Comparison against RADN, DIR, MaterialGAN and Hybrid on synthetic material.

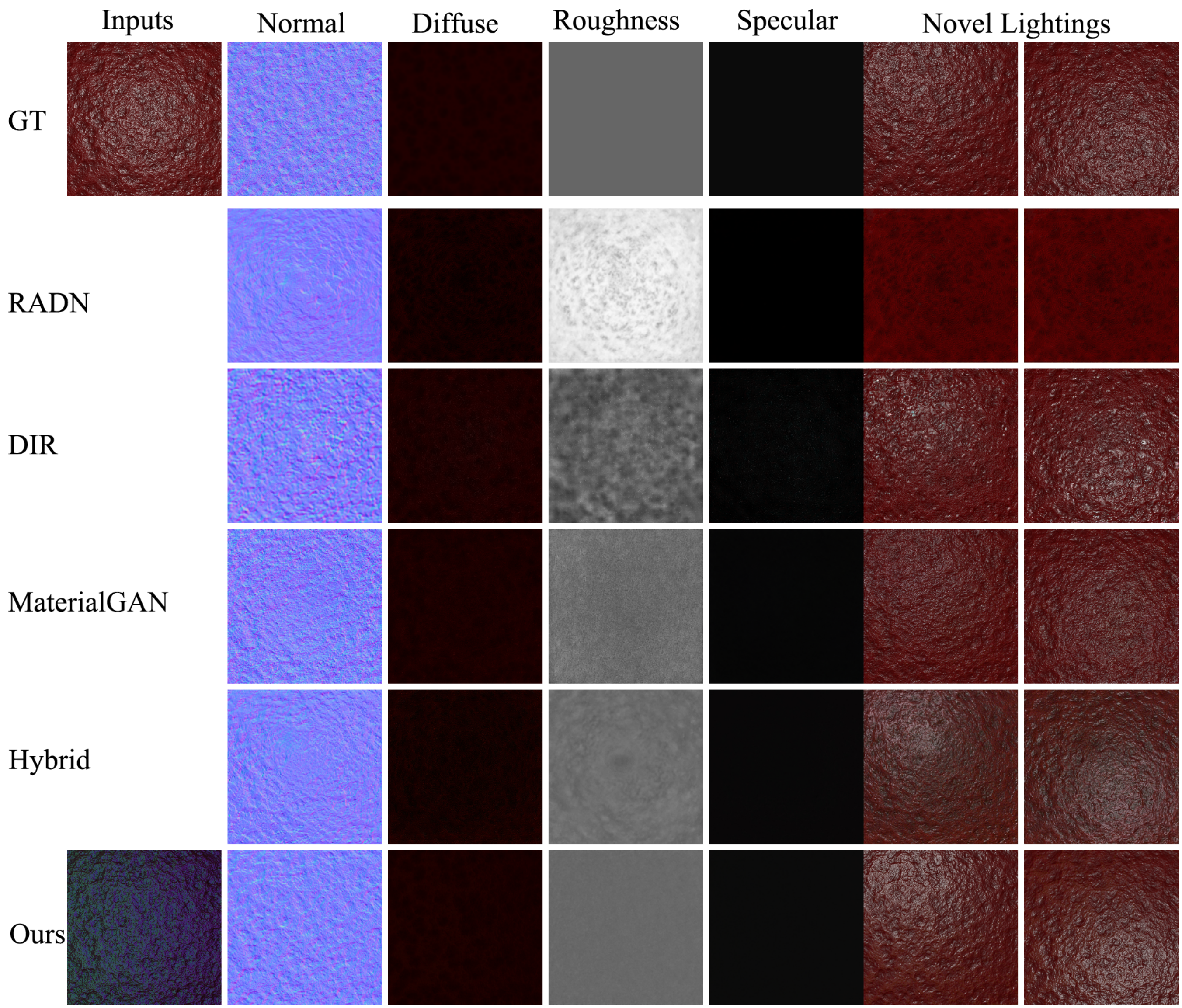

Figure 13: Comparison against RADN, DIR, MaterialGAN and Hybrid on synthetic material.

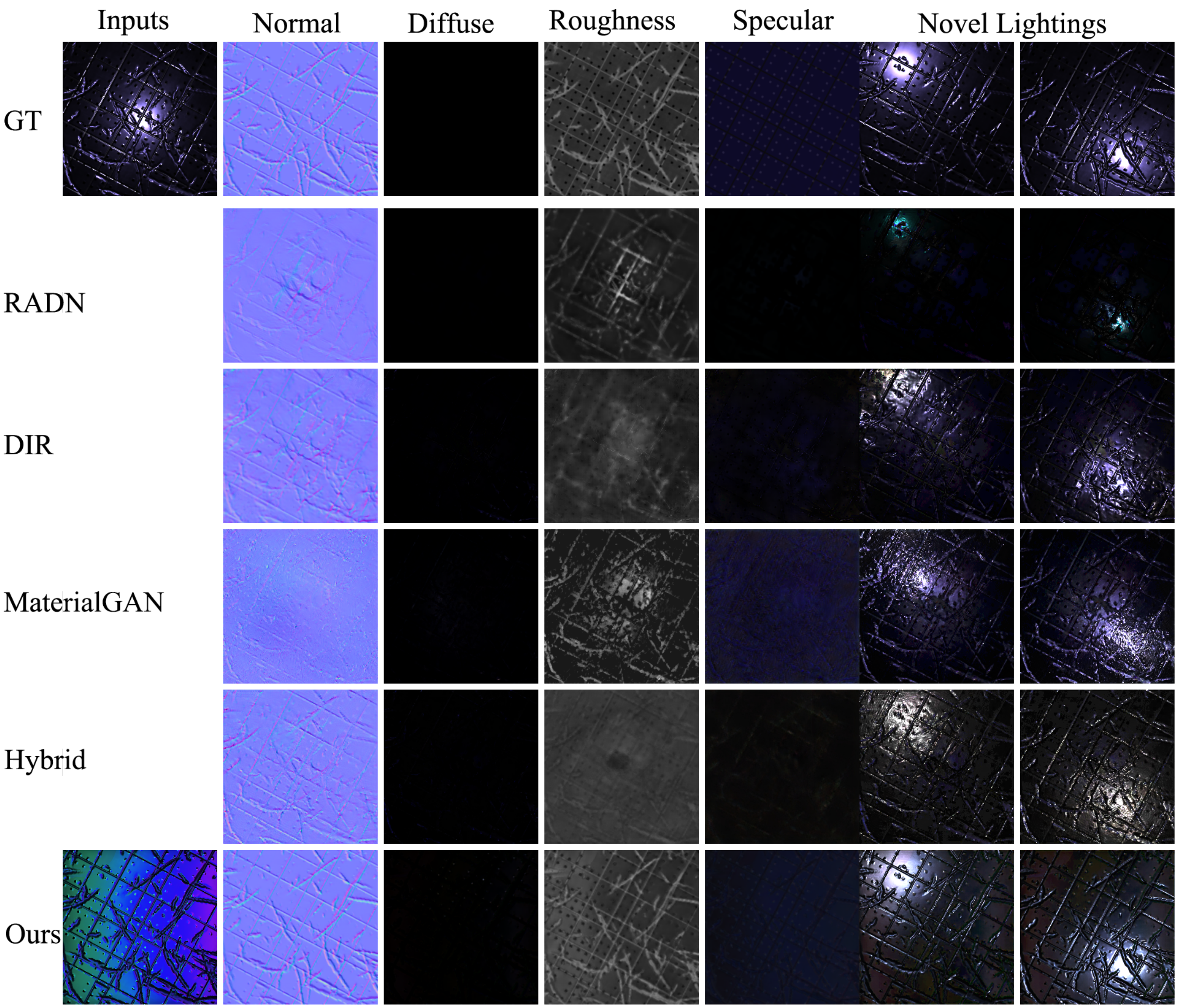

Figure 14: Comparison against RADN, DIR, MaterialGAN and Hybrid on synthetic material.

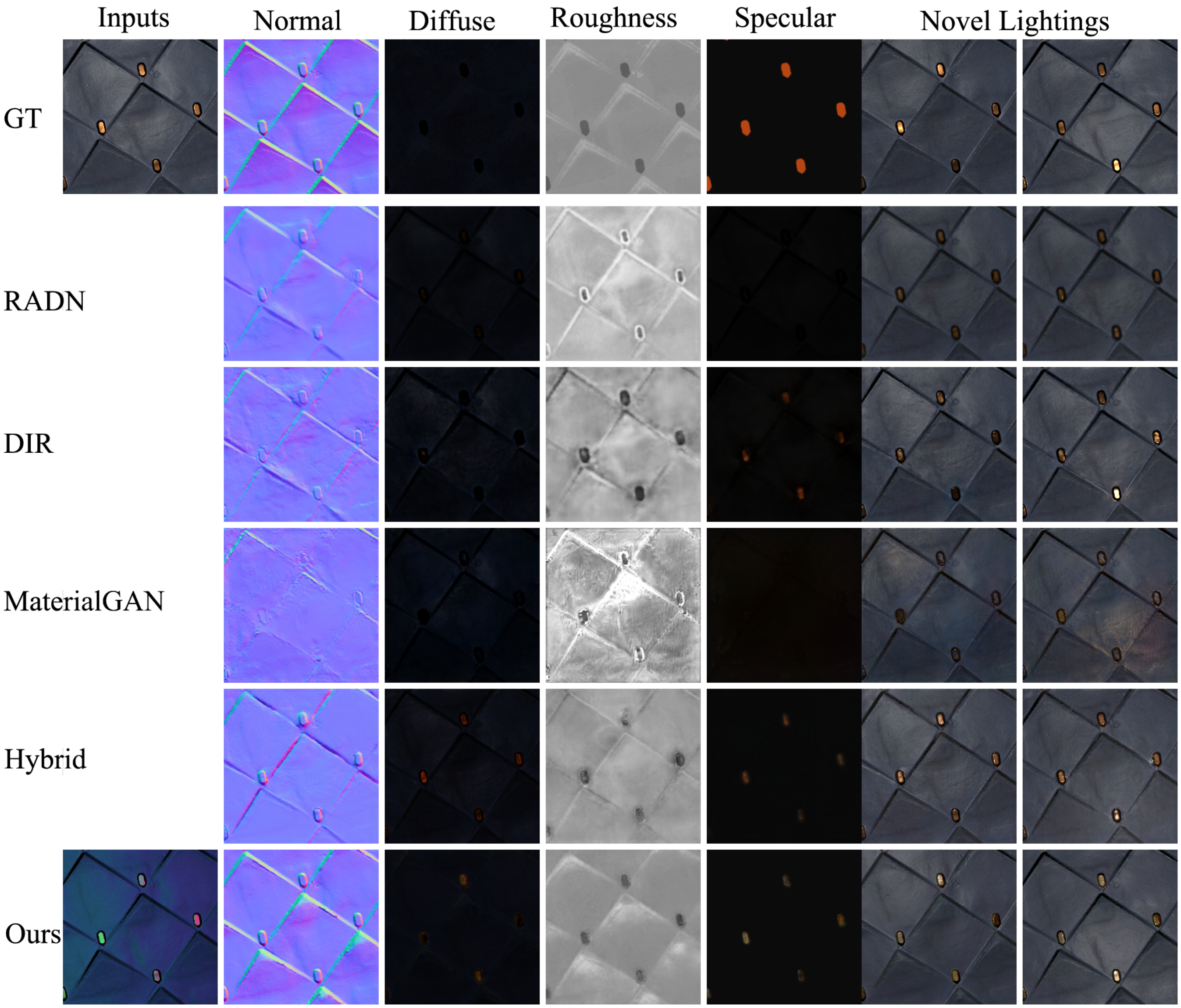

Figure 15: Comparison against RADN, DIR, MaterialGAN and Hybrid on synthetic material.

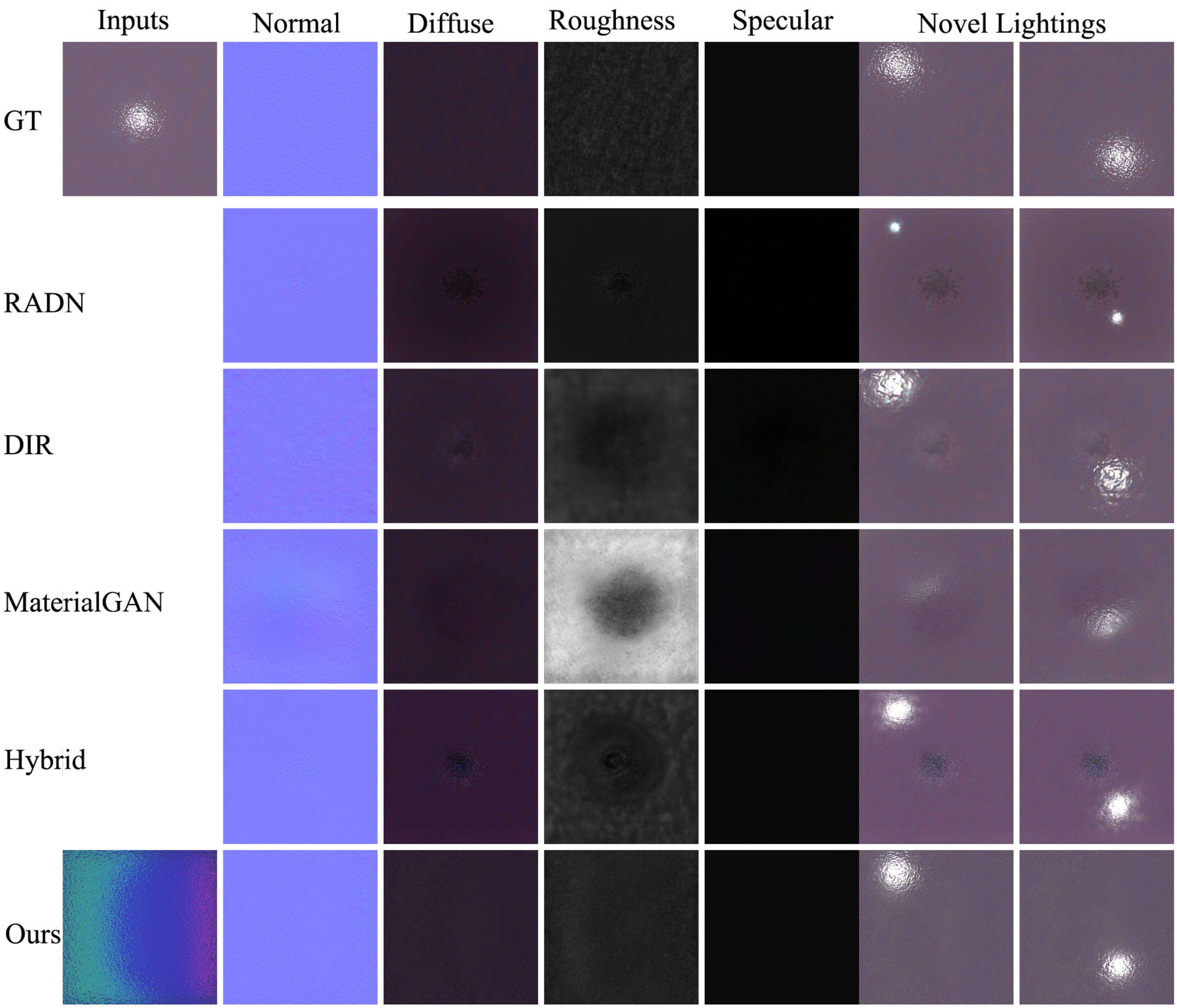

Figure 16: Comparison against RADN, DIR, MaterialGAN and Hybrid on synthetic material.

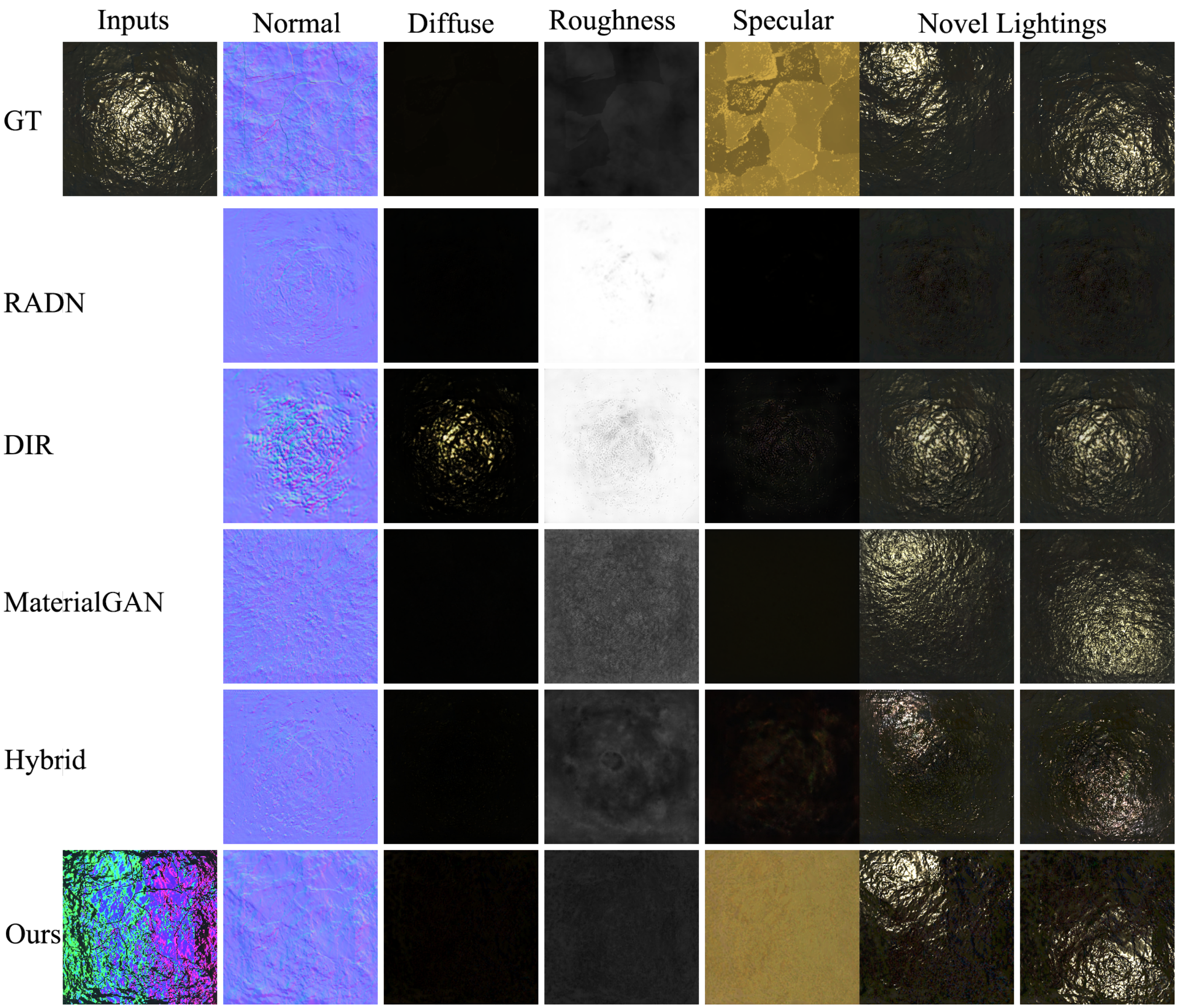

Figure 17: Comparison against RADN, DIR, MaterialGAN and Hybrid on synthetic material.

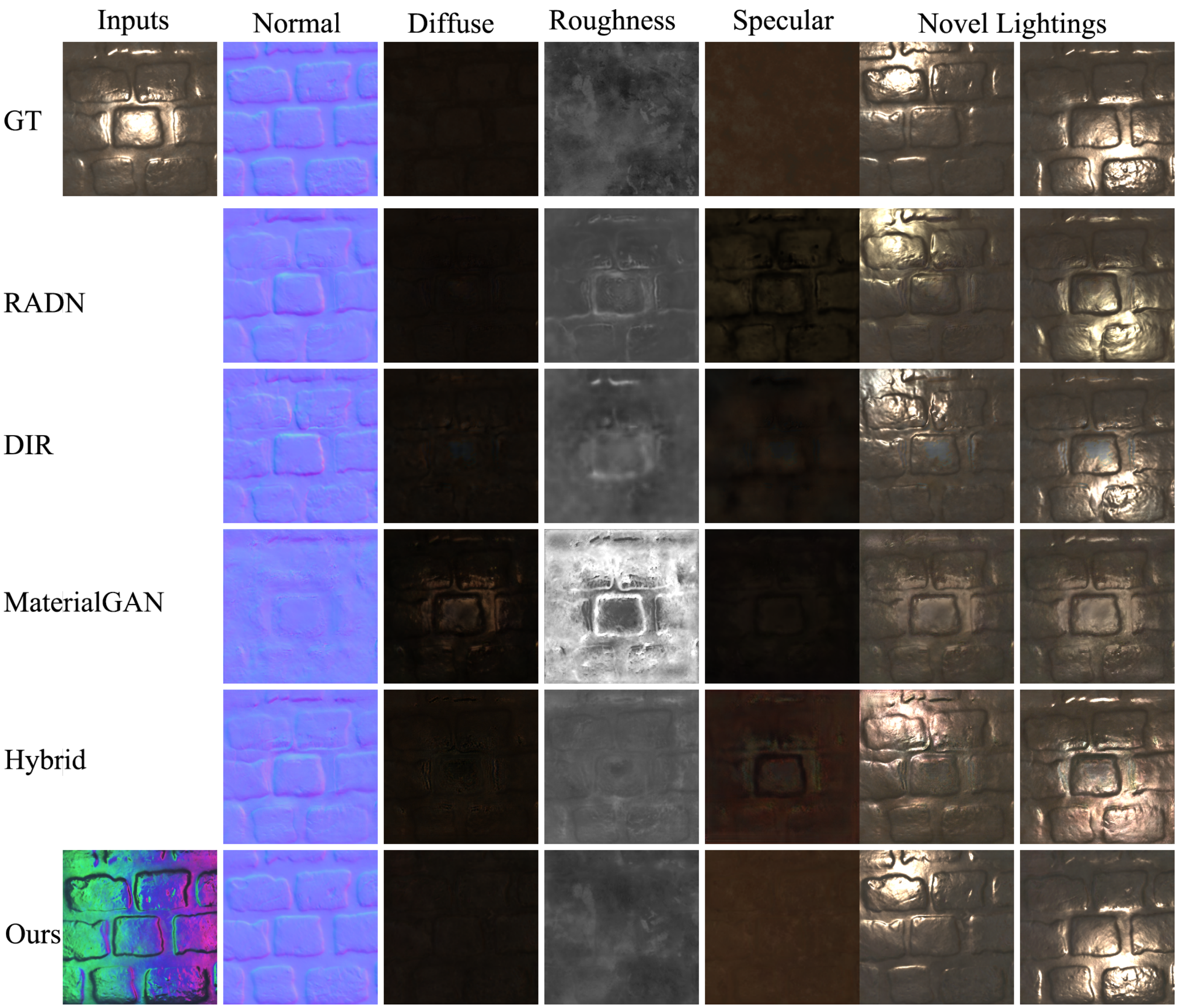

Figure 18: Comparison against RADN, DIR, MaterialGAN and Hybrid on synthetic material.