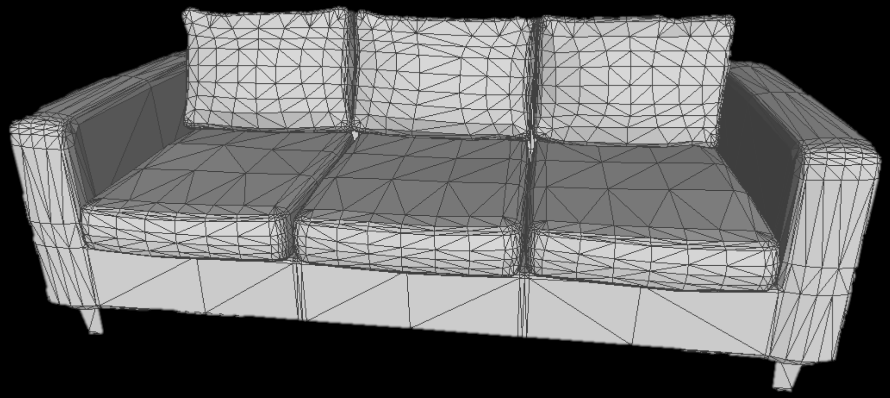
Deep Inverse Rendering for High-resolution SVBRDF Estimation from an Arbitrary Number of Images

Duan Gao [1,3], **Xiao Li** [2,3], Yue Dong [3], Pieter Peers [4], Kun Xu [1], Xin Tong [3]

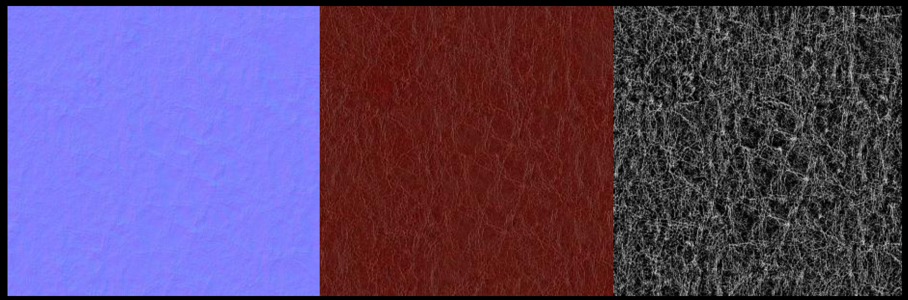
[1] Tsinghua University
[2] University of Science and Technology of China
[3] Microsoft Research Asia
[4] College of William & Mary

RENDERING

MATERIAL APPEARANCE

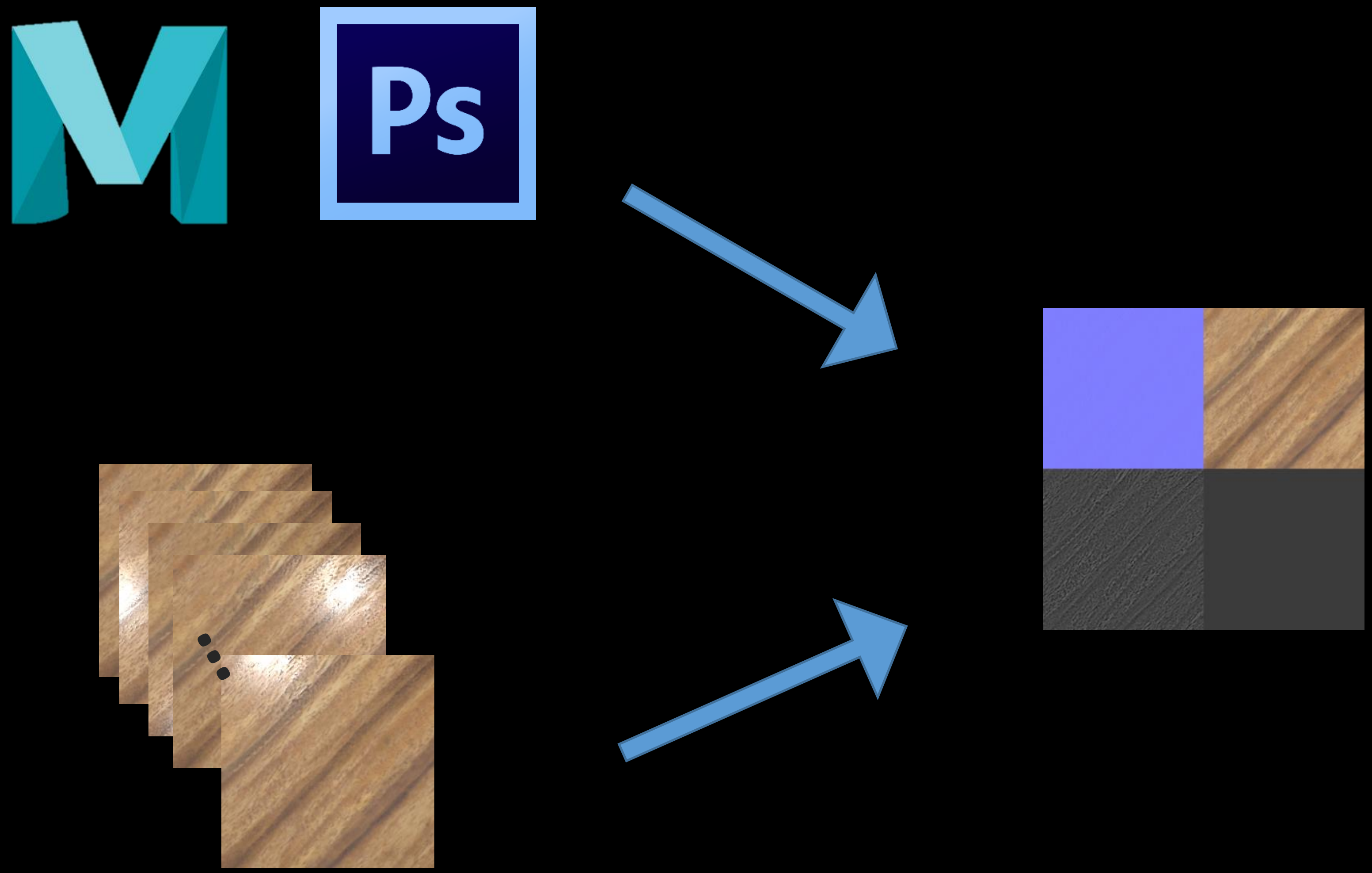


Geometry



Material

APPEARANCE ESTIMATION



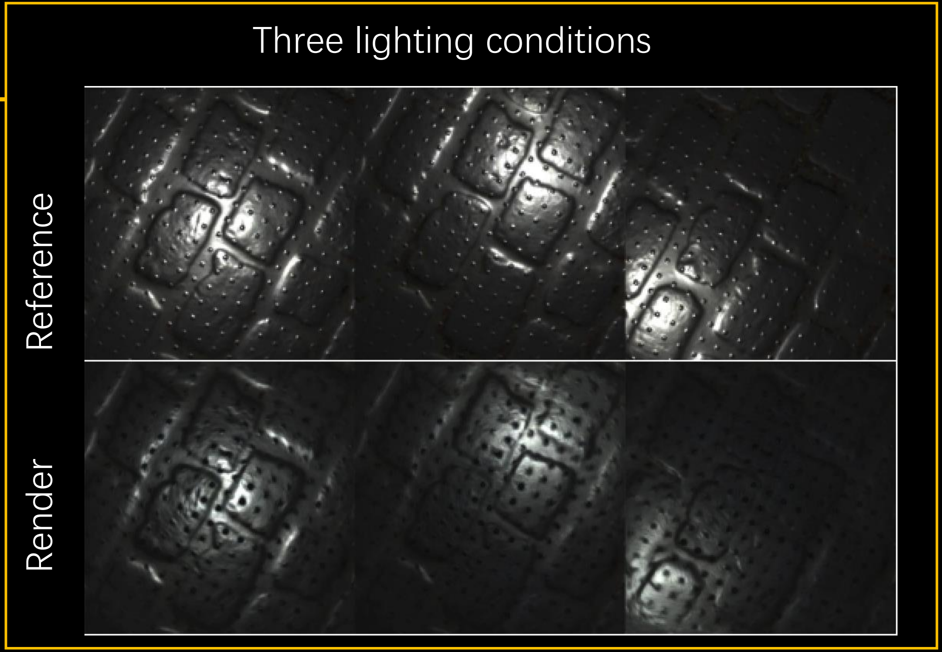
OUR GOAL

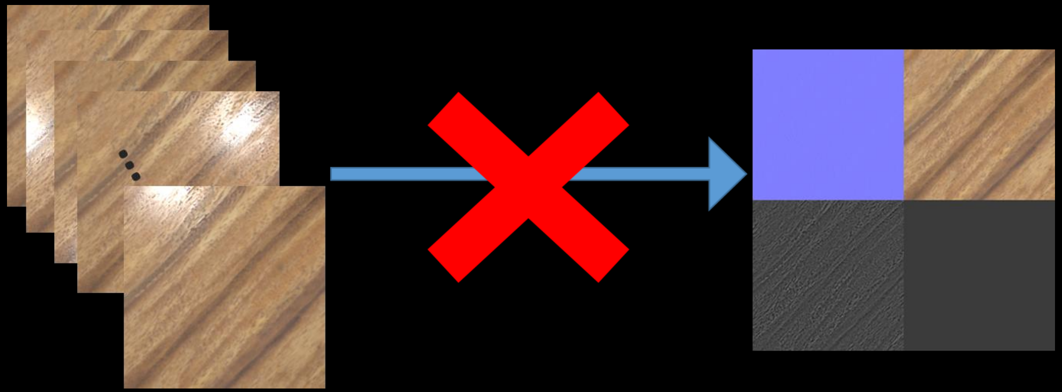
RELATED WORK

[Deschaintre et al. 2018]

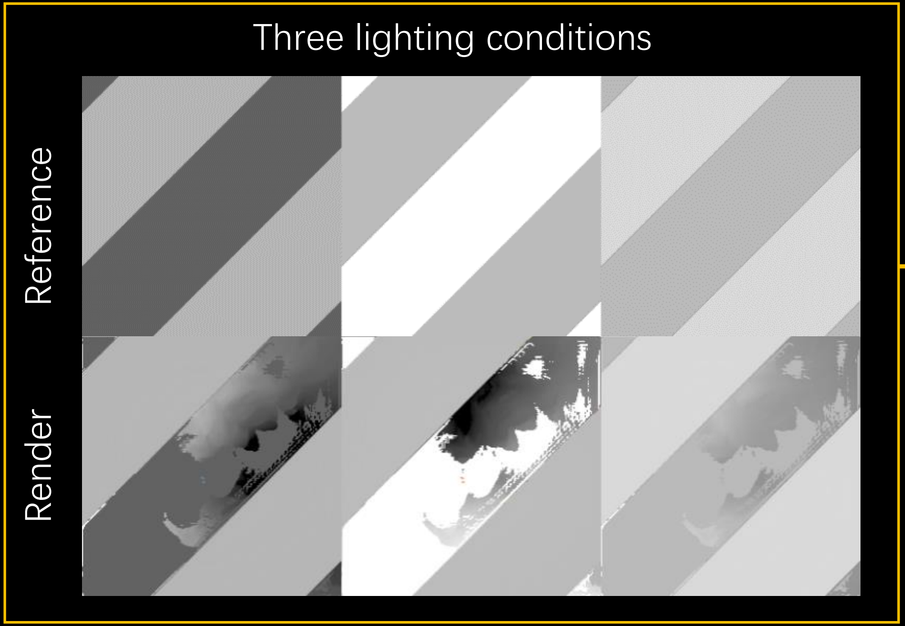
Learning-based methods

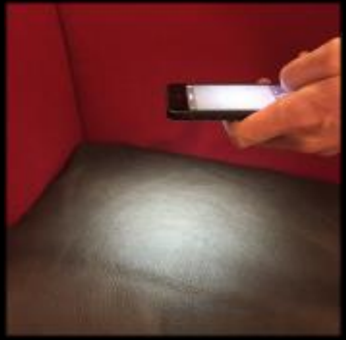
- Single input image
- Plausible





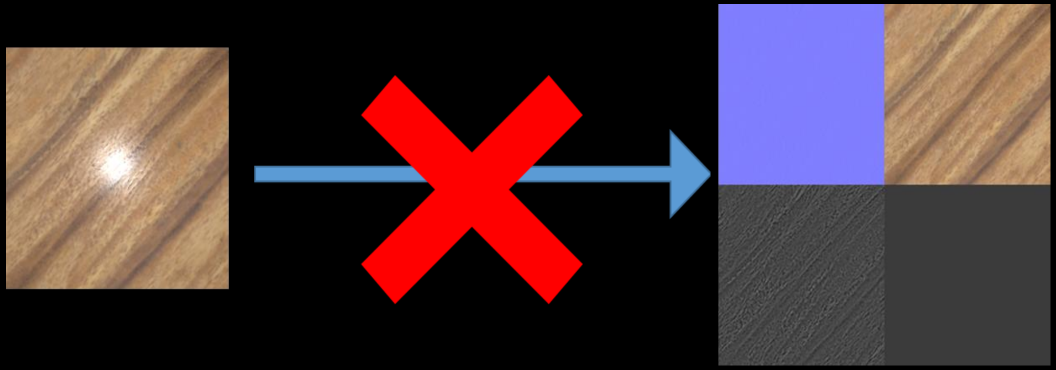
RELATED WORK





[Aittala et al. 2015]

[Dong et al. 2014]

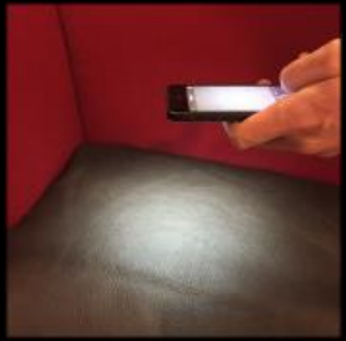


Classic Inverse Rendering

- Many input images
  (or strong assumptions)
- Accurate

RELATED WORK

[Deschaintre et al. 2018]



[Aittala et al. 2015]

[Dong et al. 2014]

single

few

many

Number of input images

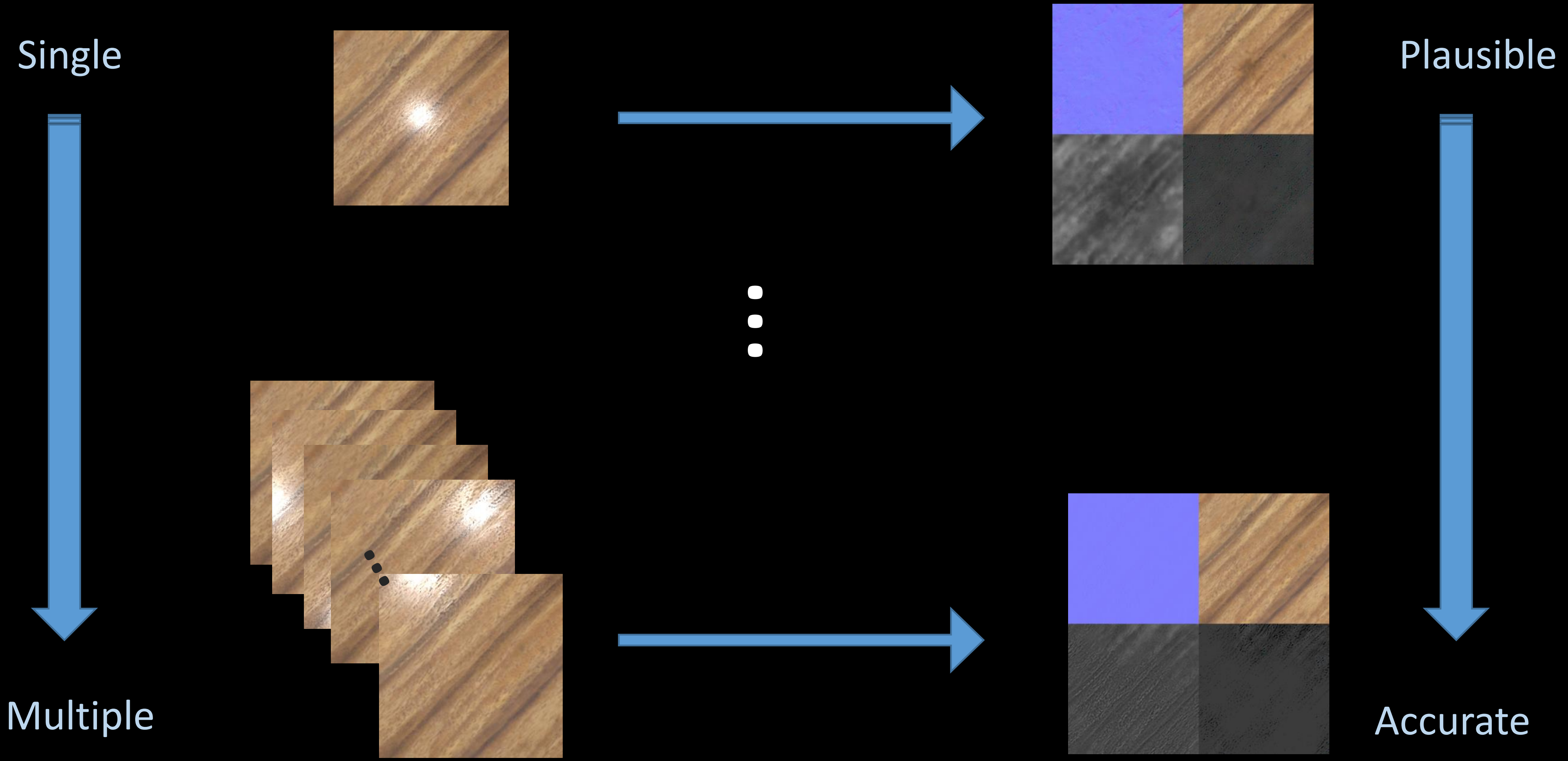
Learning-based methods

- Single input image
- Plausible

Classic Inverse Rendering

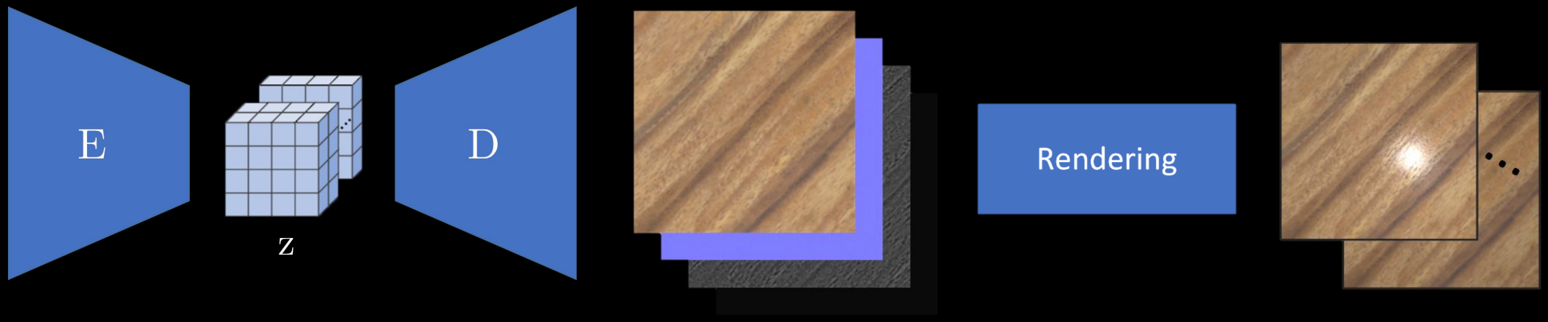
- Many input images
  (or strong assumptions)
- Accurate

OUR CONTRIBUTION



OUR METHOD

Key Idea: Deep Inverse Rendering



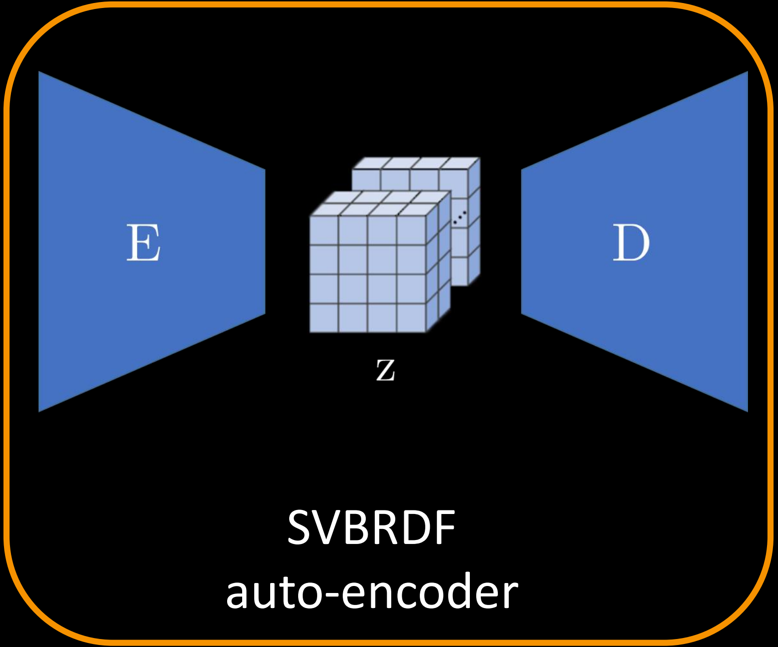
SVBRDF auto-encoder

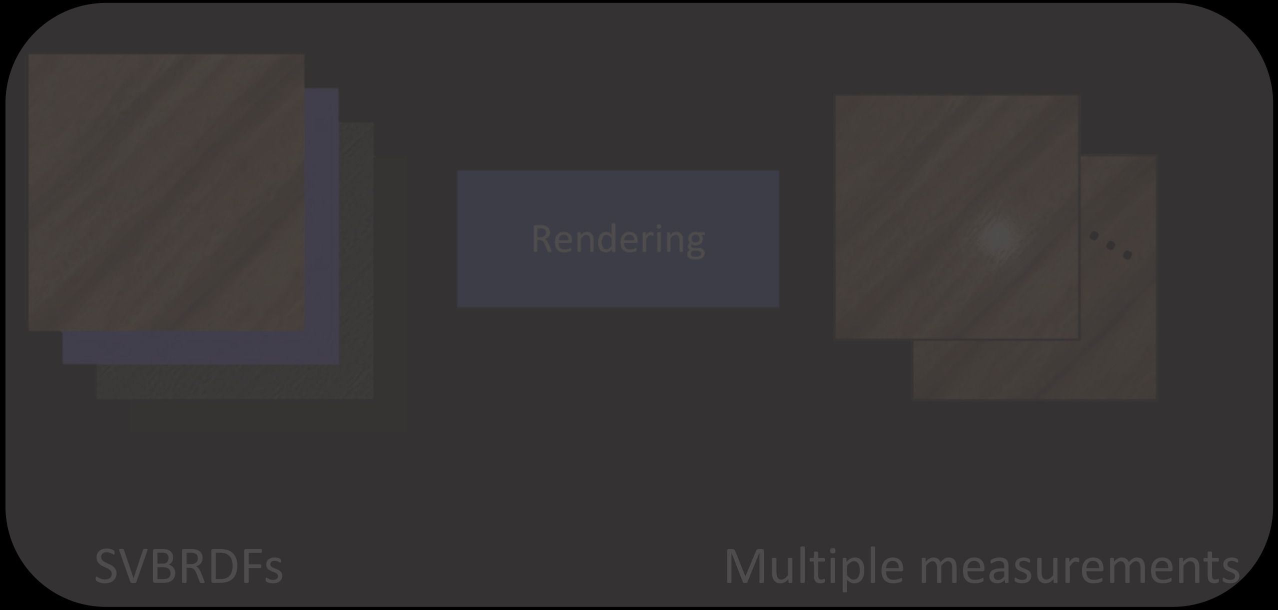
SVBRDFs

Multiple measurements

OUR METHOD

Key Idea: Deep Inverse Rendering

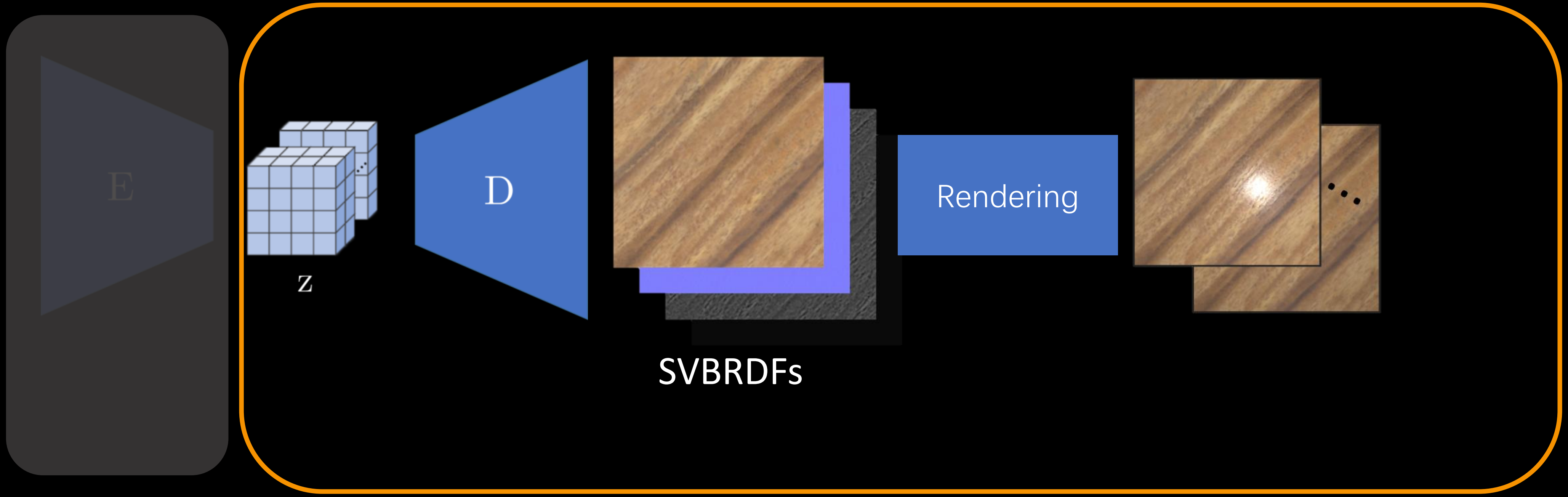




OUR METHOD

Key Idea: Deep Inverse Rendering

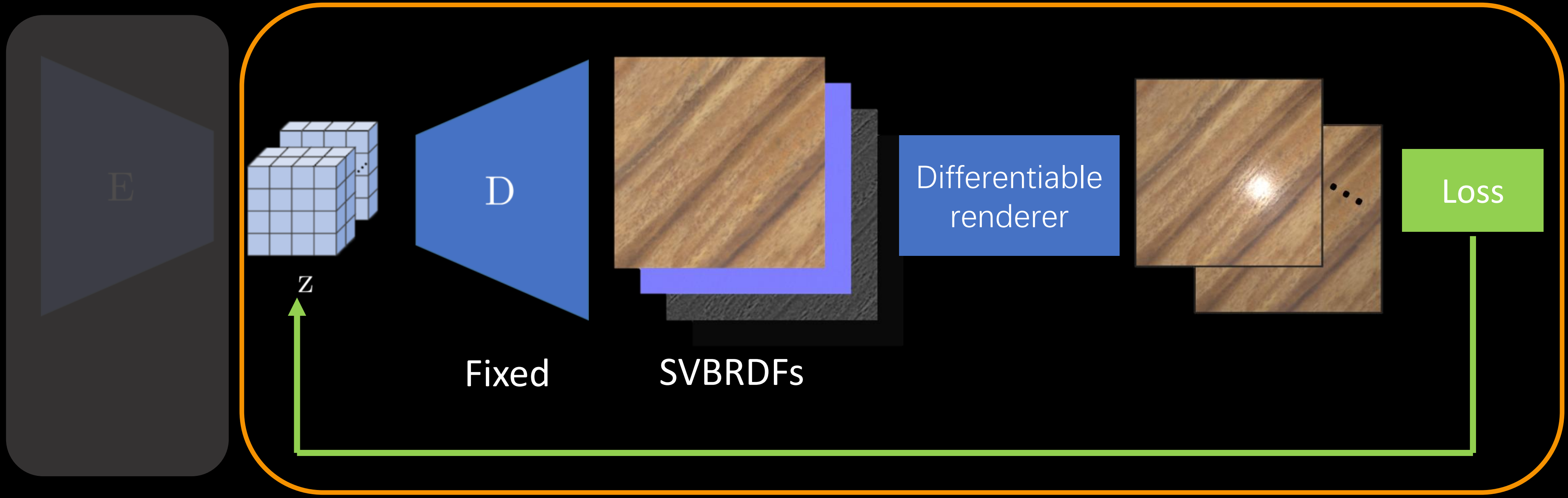
- Optimize in learned latent space



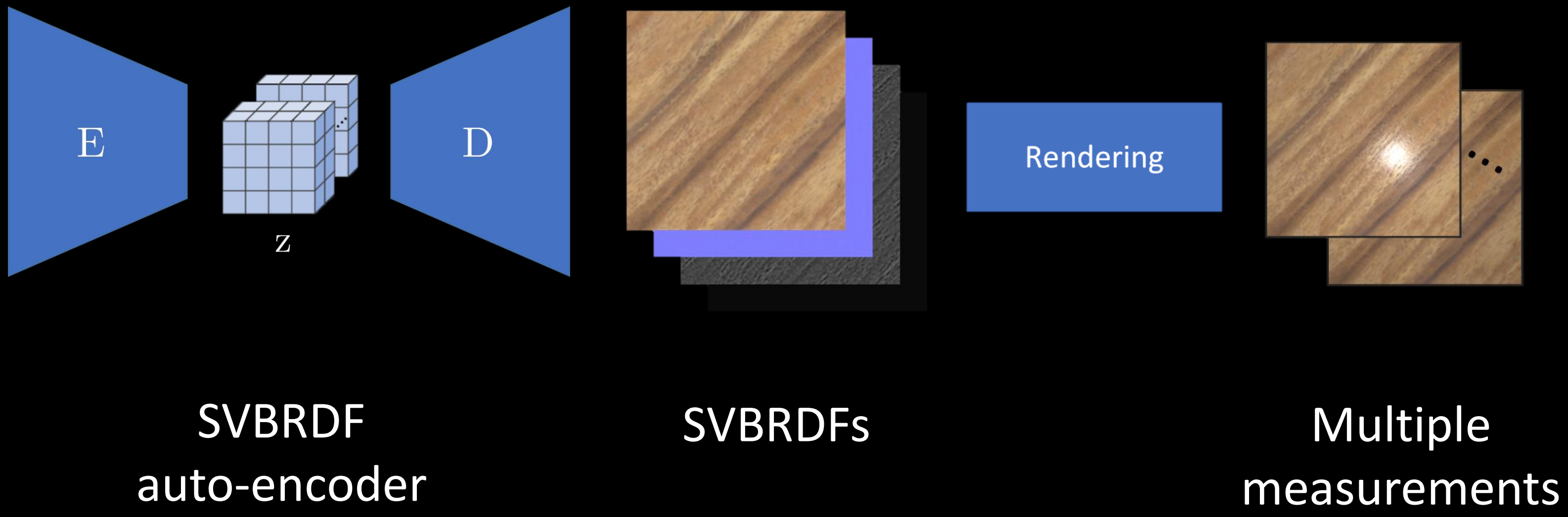
OUR METHOD

Key Idea: Deep Inverse Rendering

- Optimize in learned latent space



KEY CHALLENGES



KEY CHALLENGES

- **How to set correct error metric to preserve quality coherence of different maps?**

- **How to construct a smooth space suitable for optimization?**

- **How to get a good initialization?**

KEY CHALLENGES

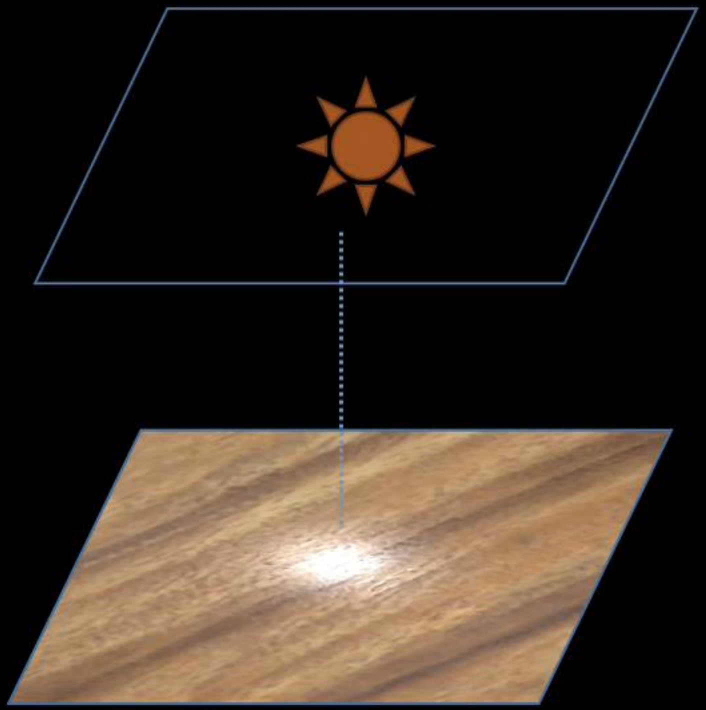
- Training Loss

- Smoothness regularization

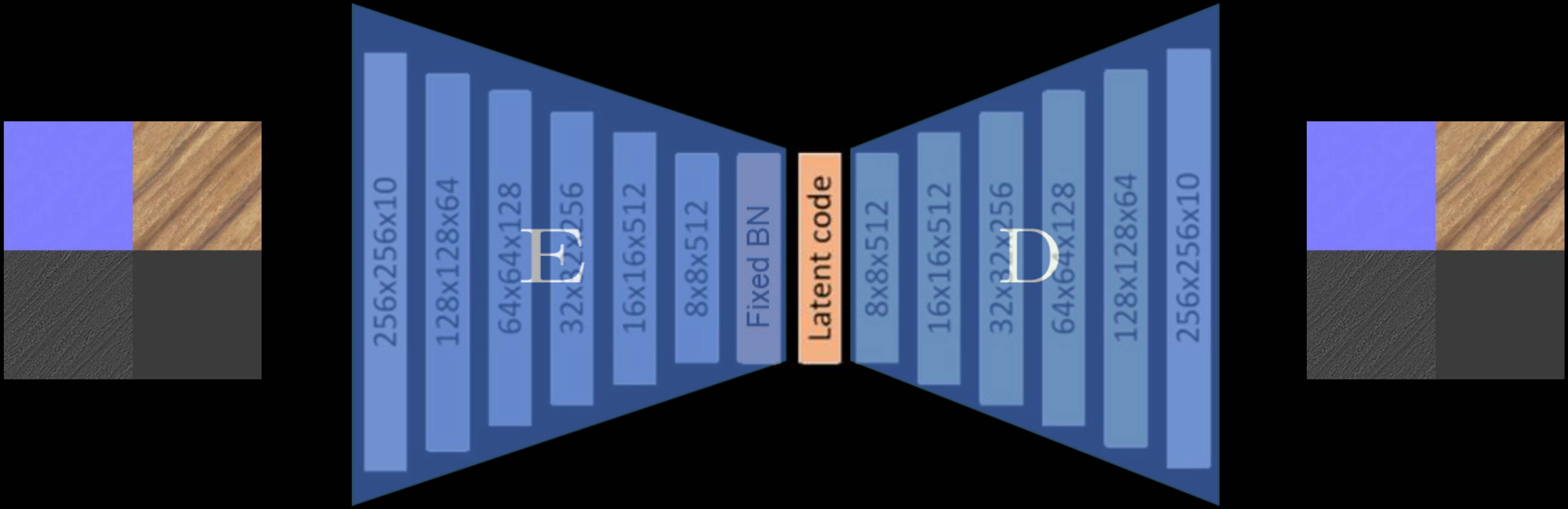
- Initialization strategy

ASSUMPTIONS

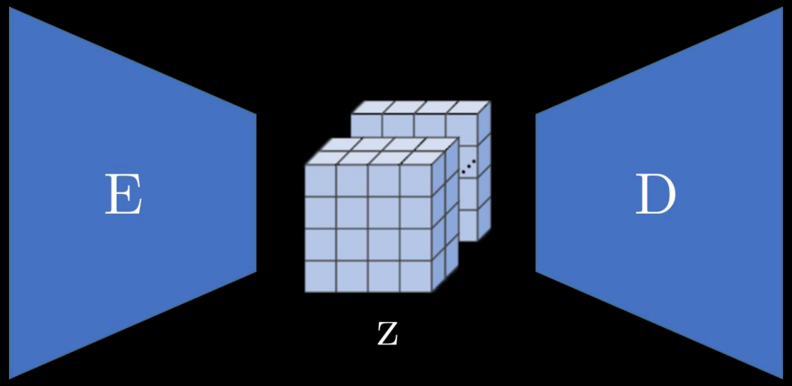
- Planar object
- Point light source collocated with the camera
- Fix distance between object plane and camera



SVBRDF AUTO-ENCODER



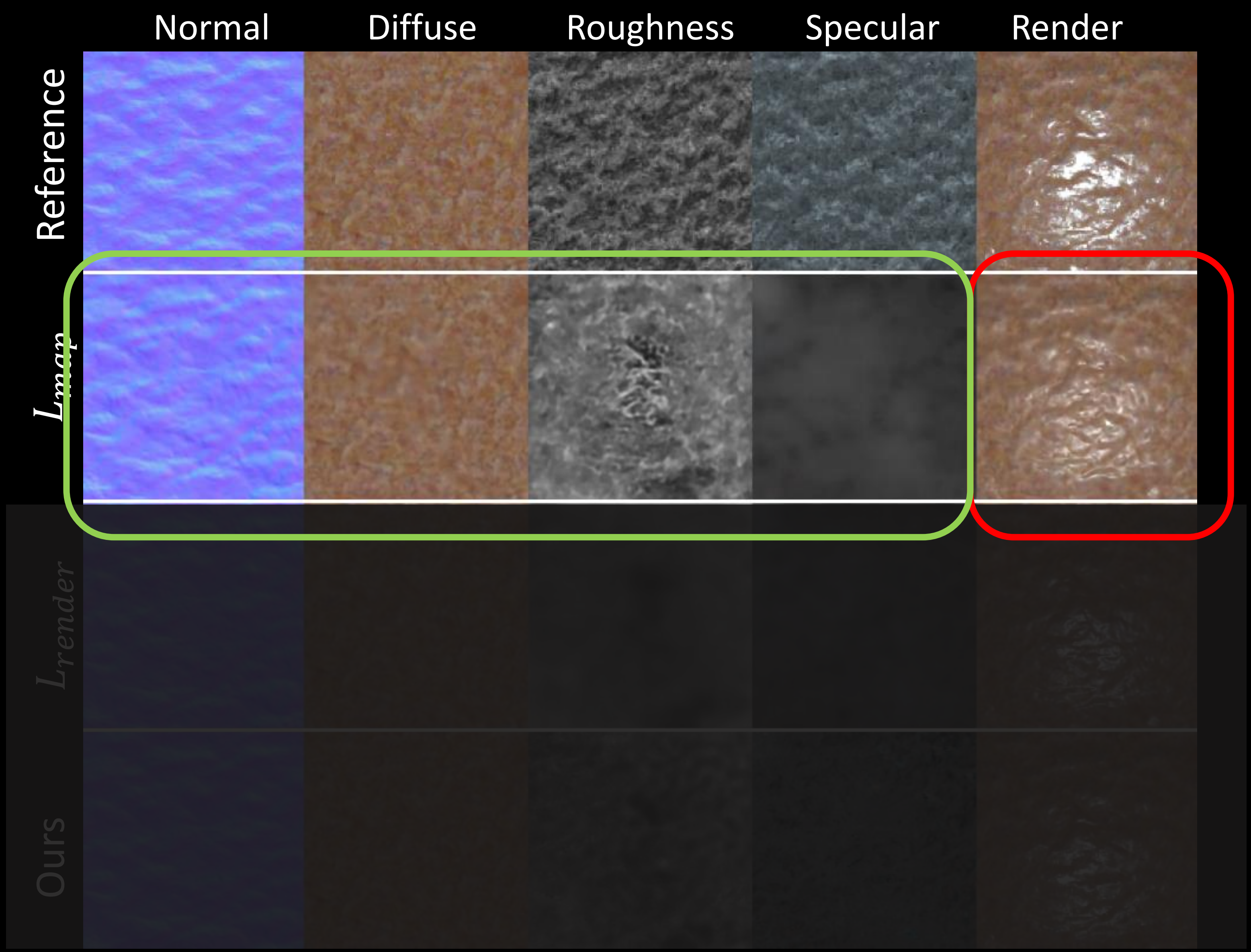
TRAINING SVBRDF AUTO-ENCODER



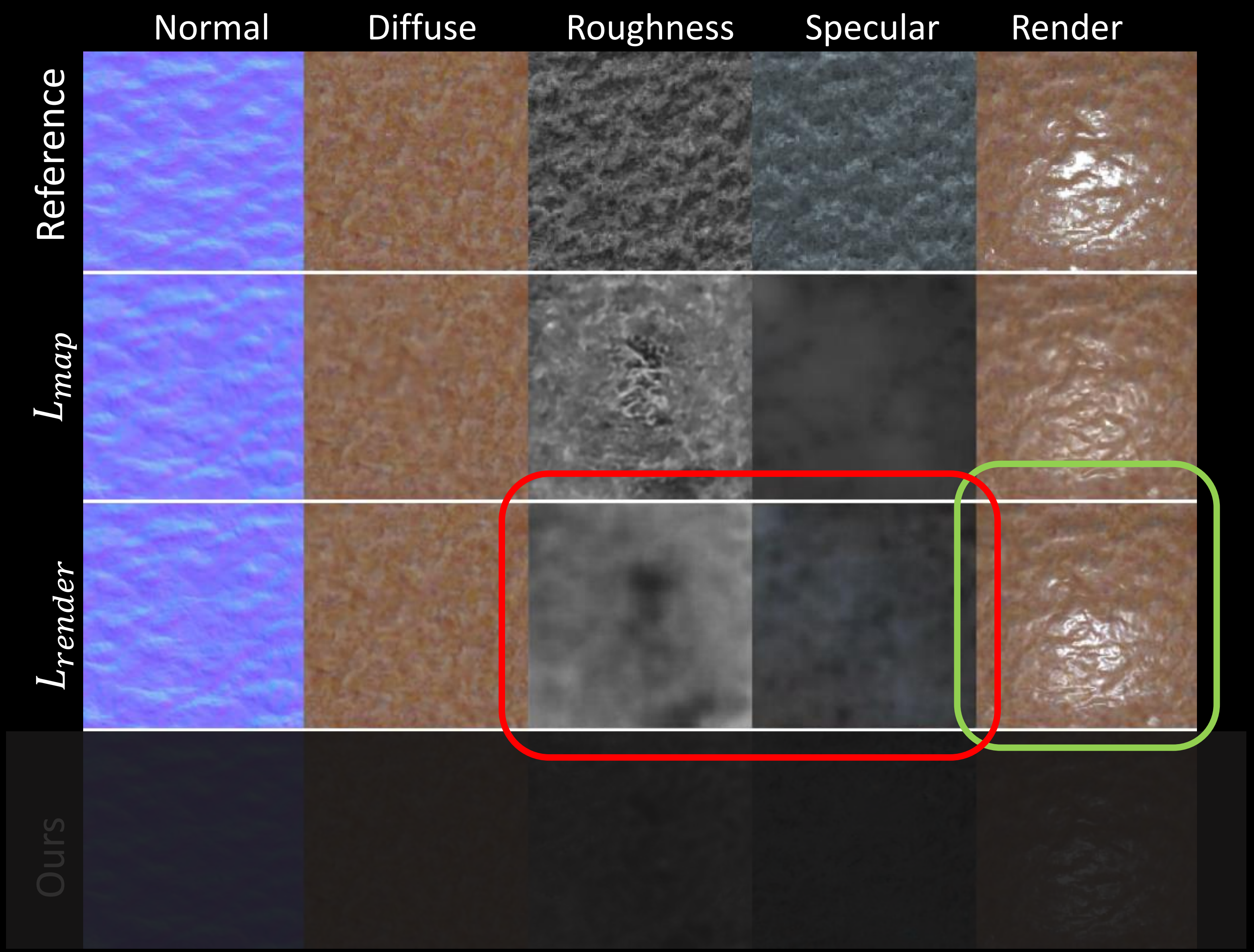
Training Loss:

$$\mathcal{L}_{train} = \mathcal{L}_{map} + \lambda_{render} \mathcal{L}_{render}$$

TRAINING SVBRDF AUTO-ENCODER



TRAINING SVBRDF AUTO-ENCODER



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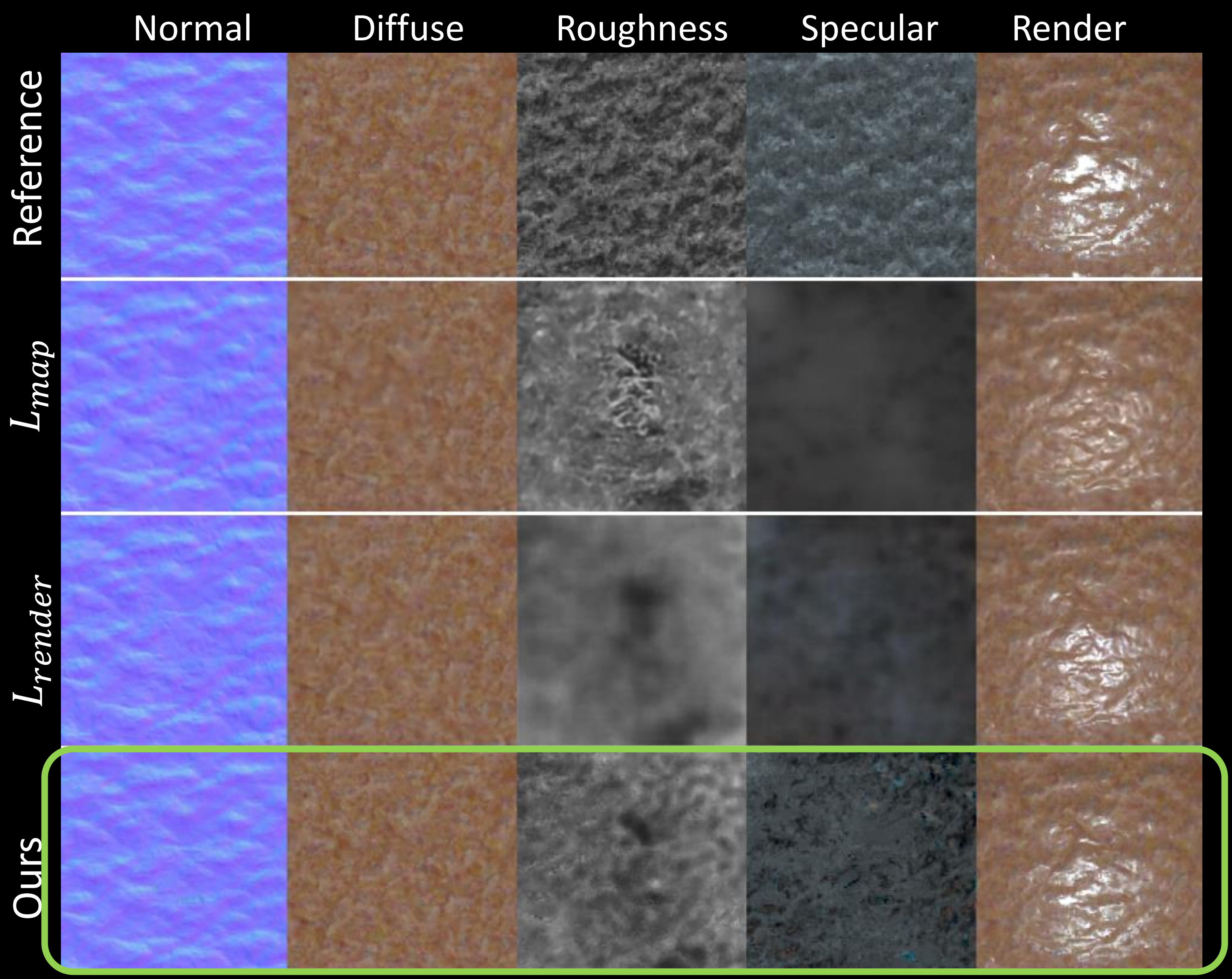

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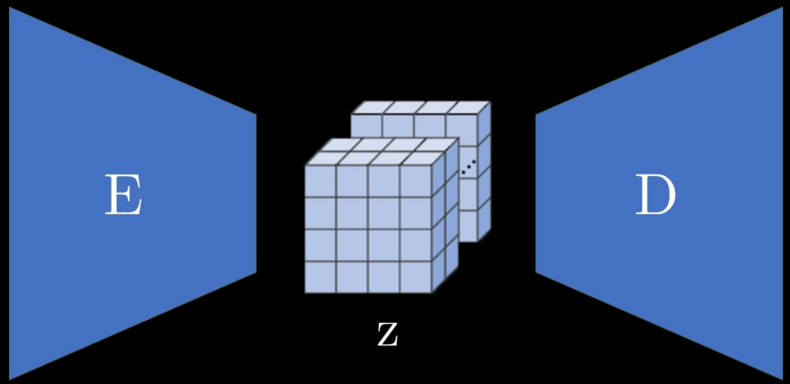


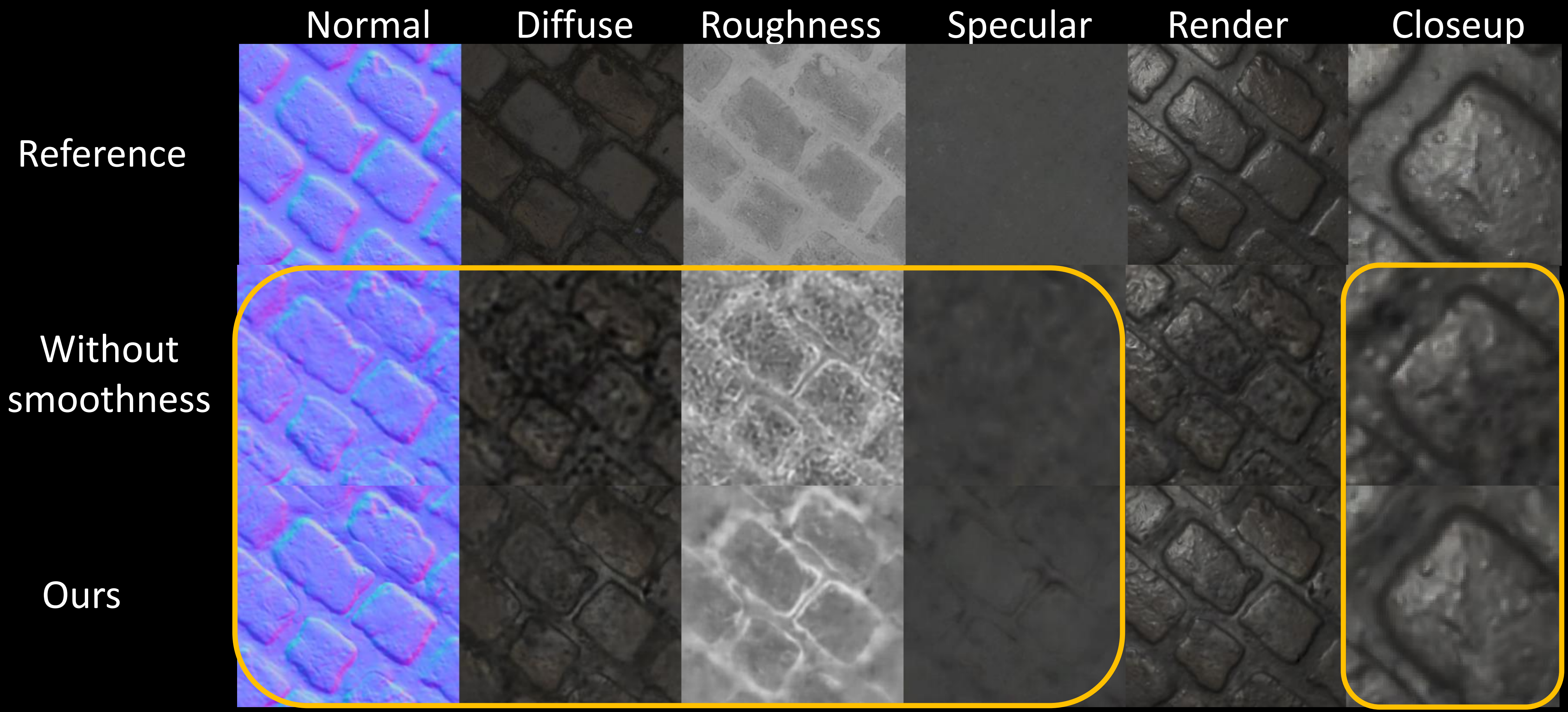
Training Loss:

$$\mathcal{L}_{train} = \mathcal{L}_{map} + \lambda_{render}\mathcal{L}_{render}$$

Latent space smoothness:

$$\mathcal{L}_{smooth} = \lambda_{smooth}||D(z) - D(z+\xi)||_1$$

TRAINING SVBRDF AUTO-ENCODER



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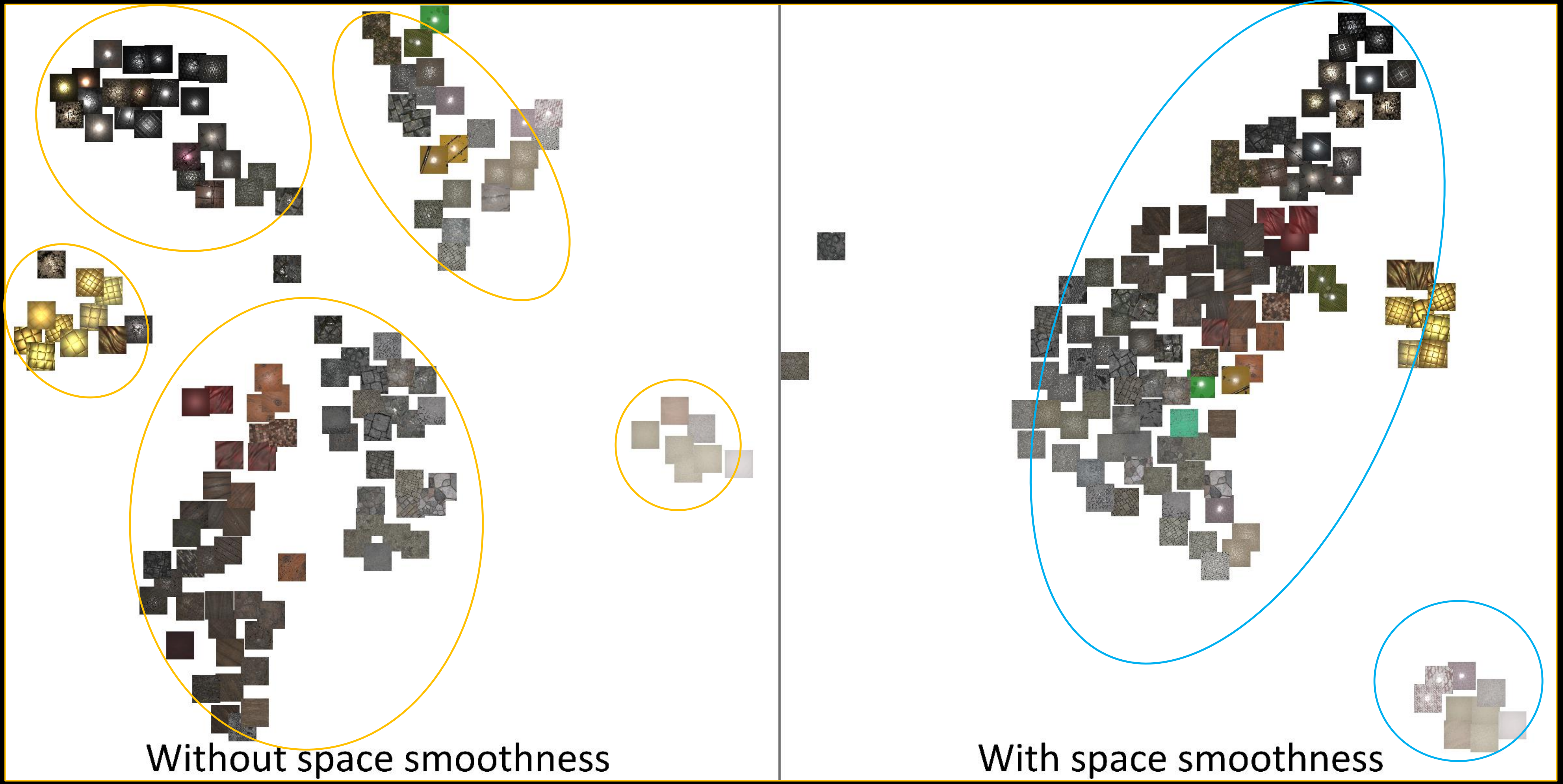
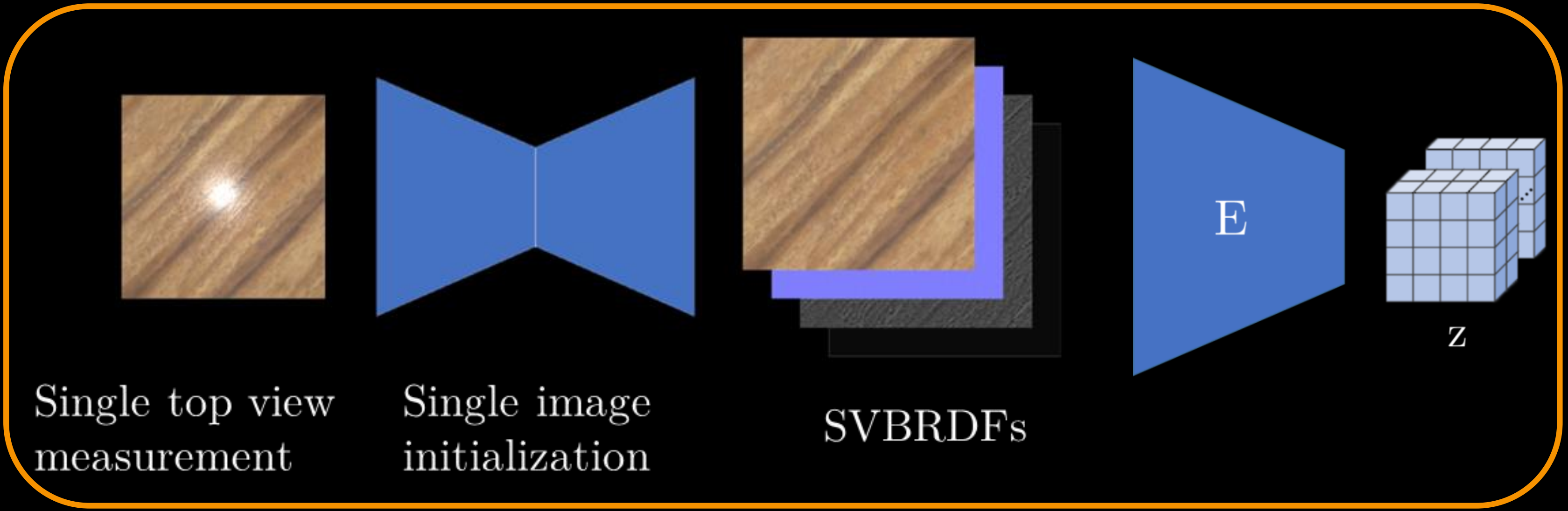
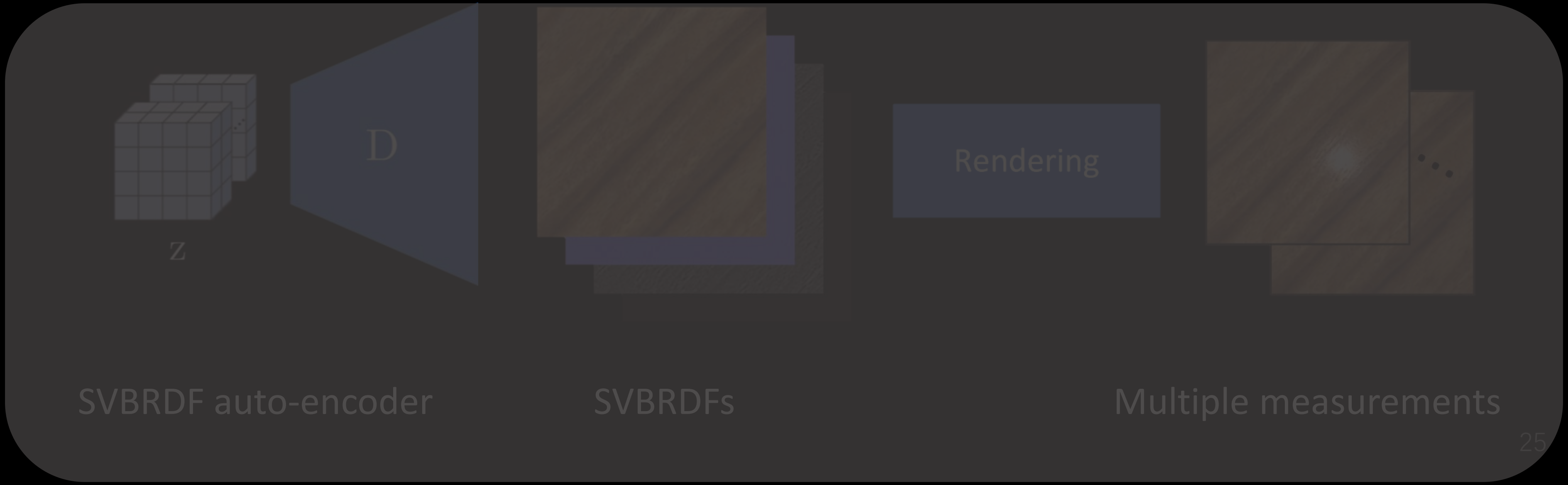


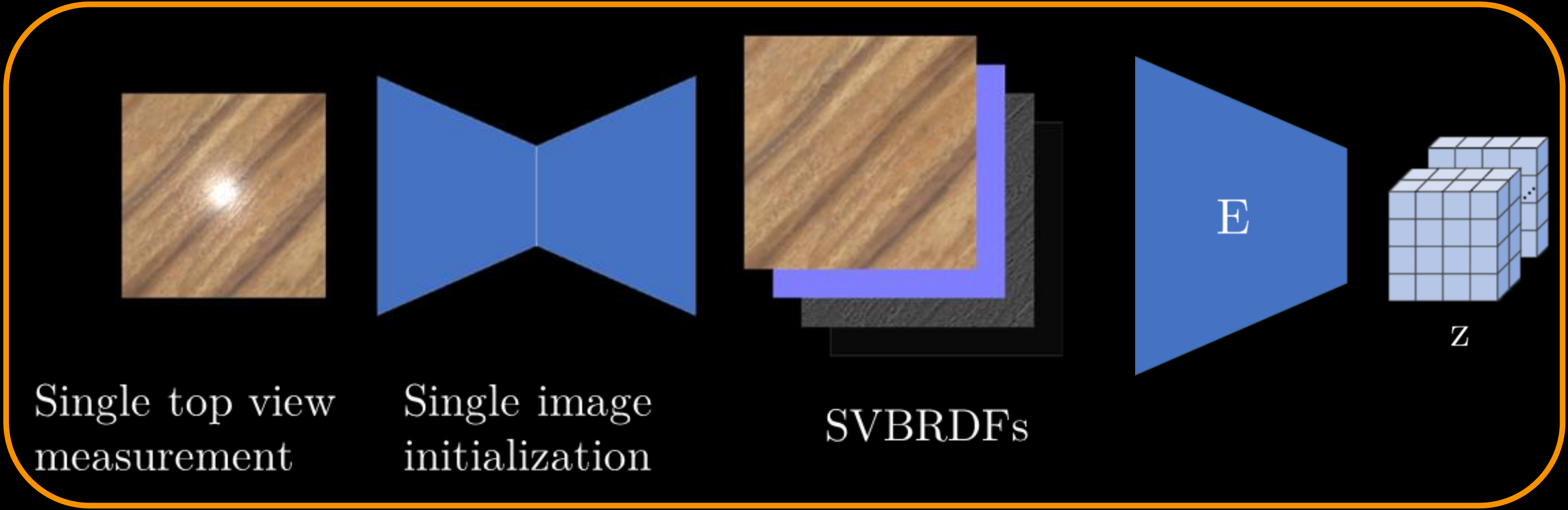
BOOTSTRAP THE OPTIMIZATION



State-of-the art single input network [Deschaintre et al. 2018]

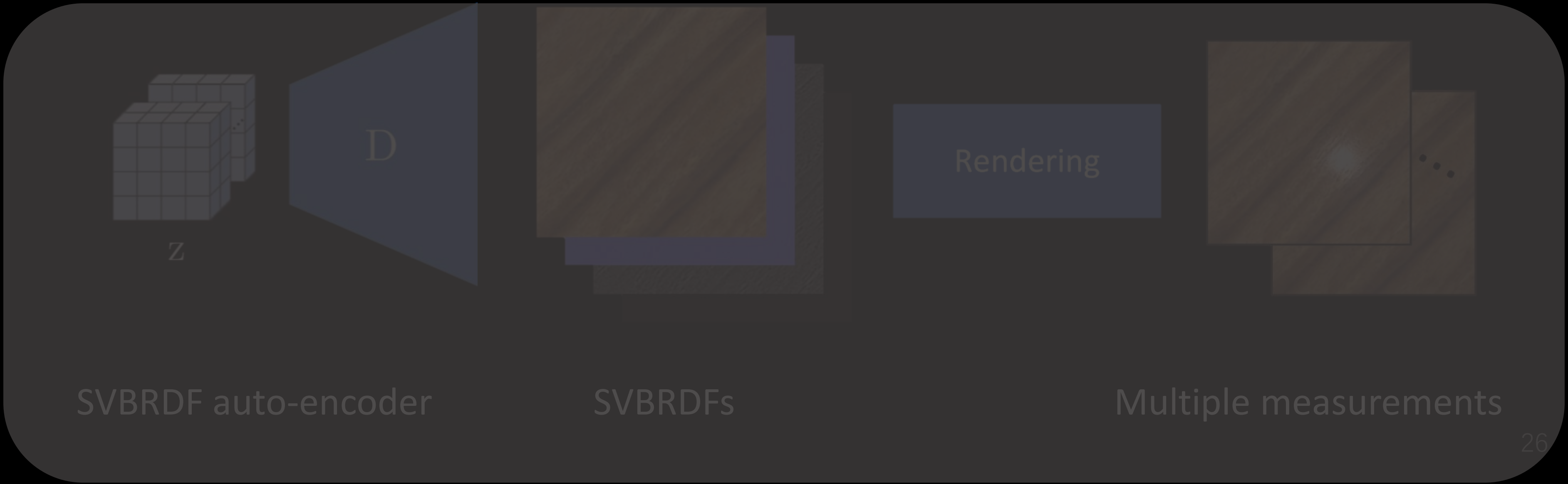


BOOTSTRAP THE OPTIMIZATION

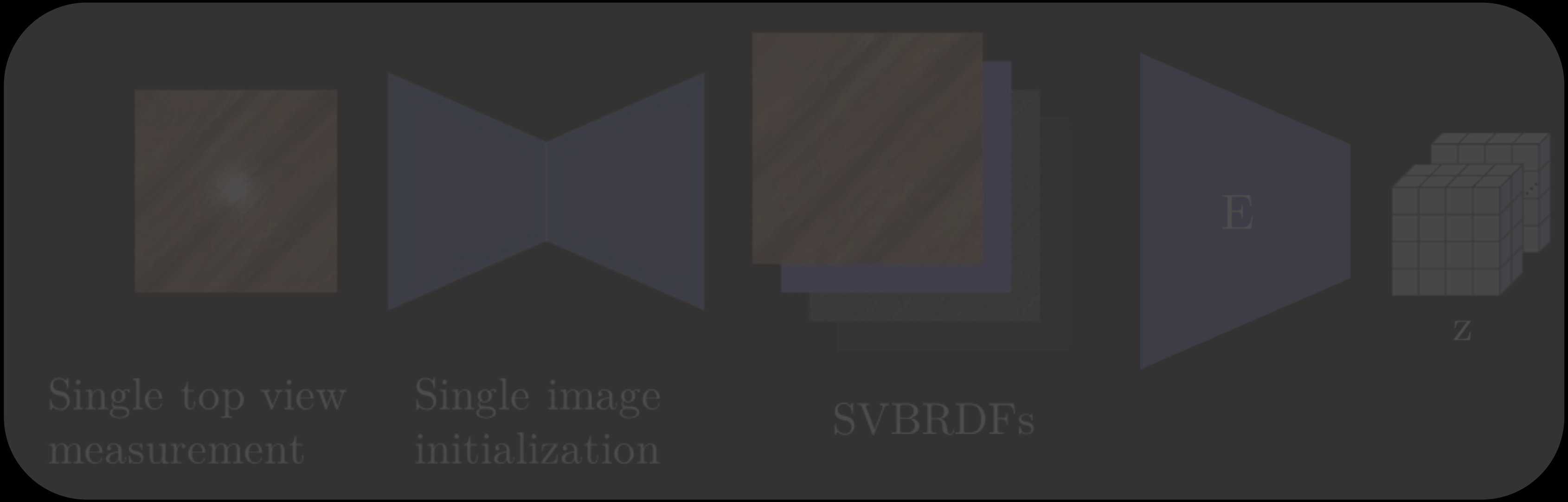


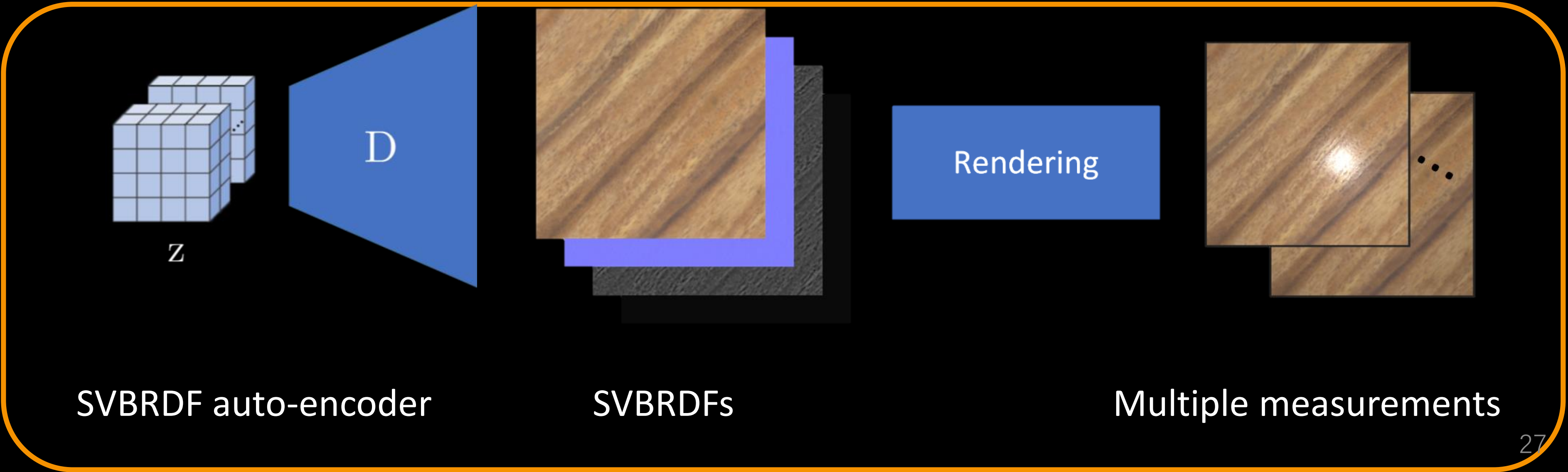
State-of-the art single input network [Deschaintre et al. 2018]

Or any other state-of-the art methods!

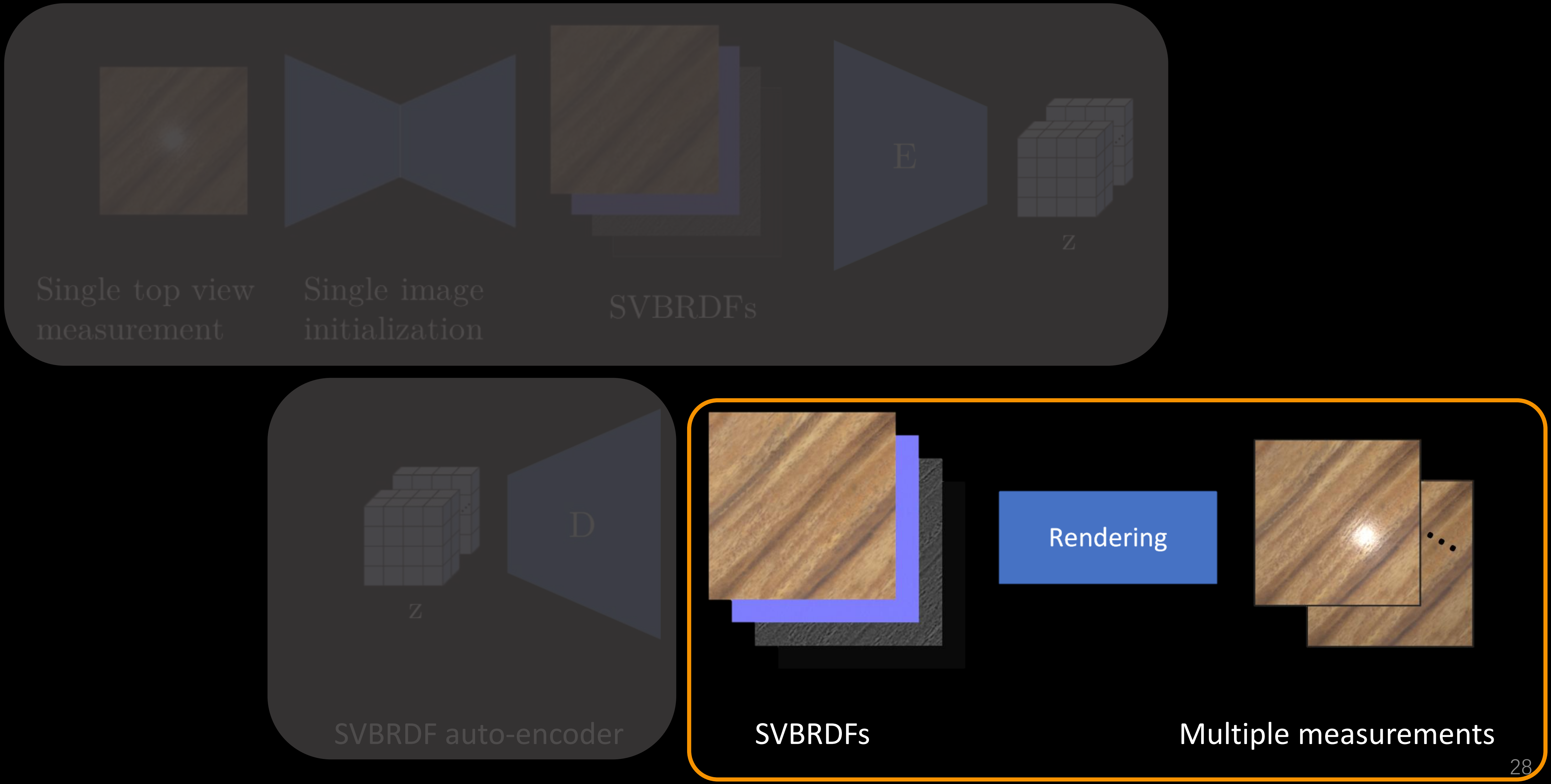


OPTIMIZE IN LATENT SPACE

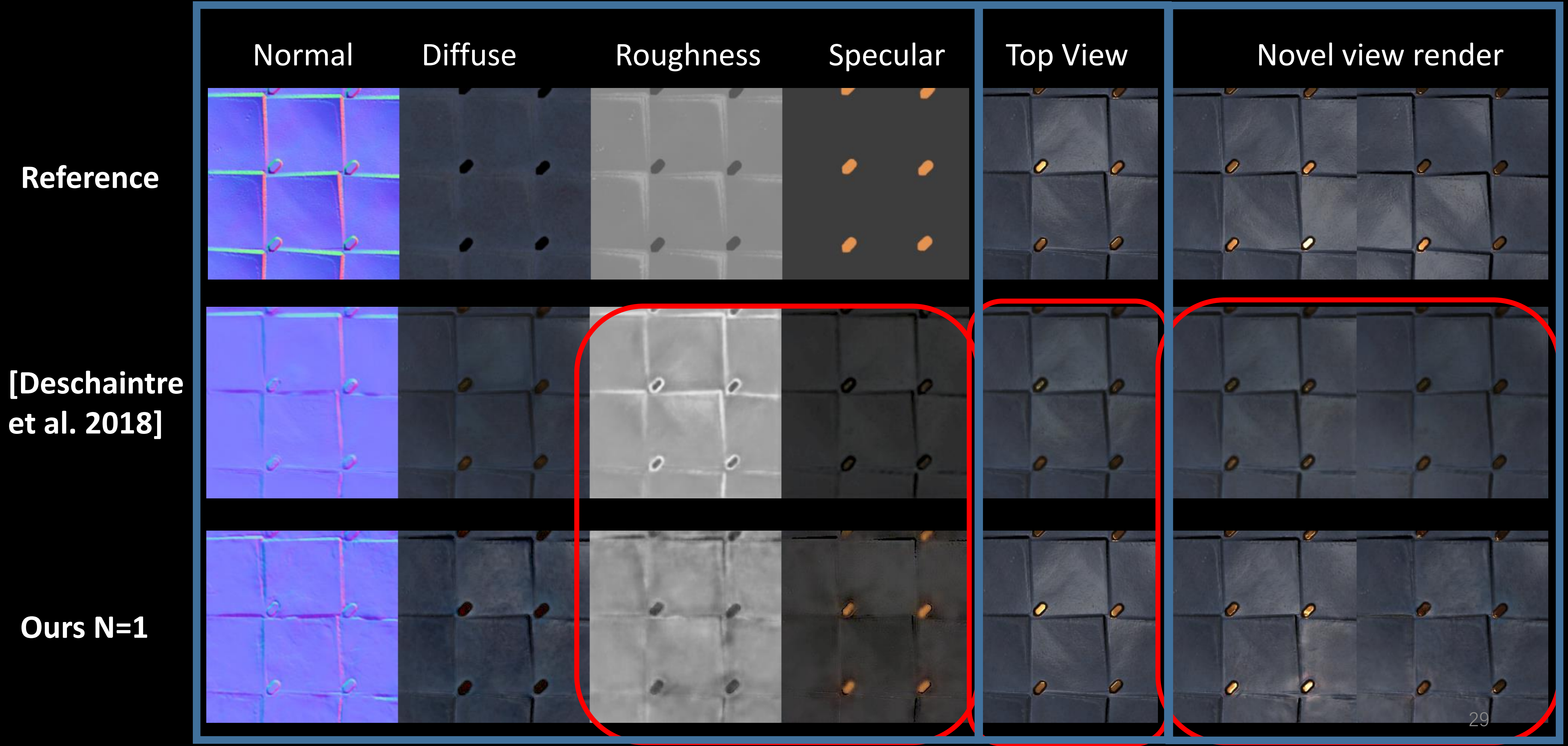


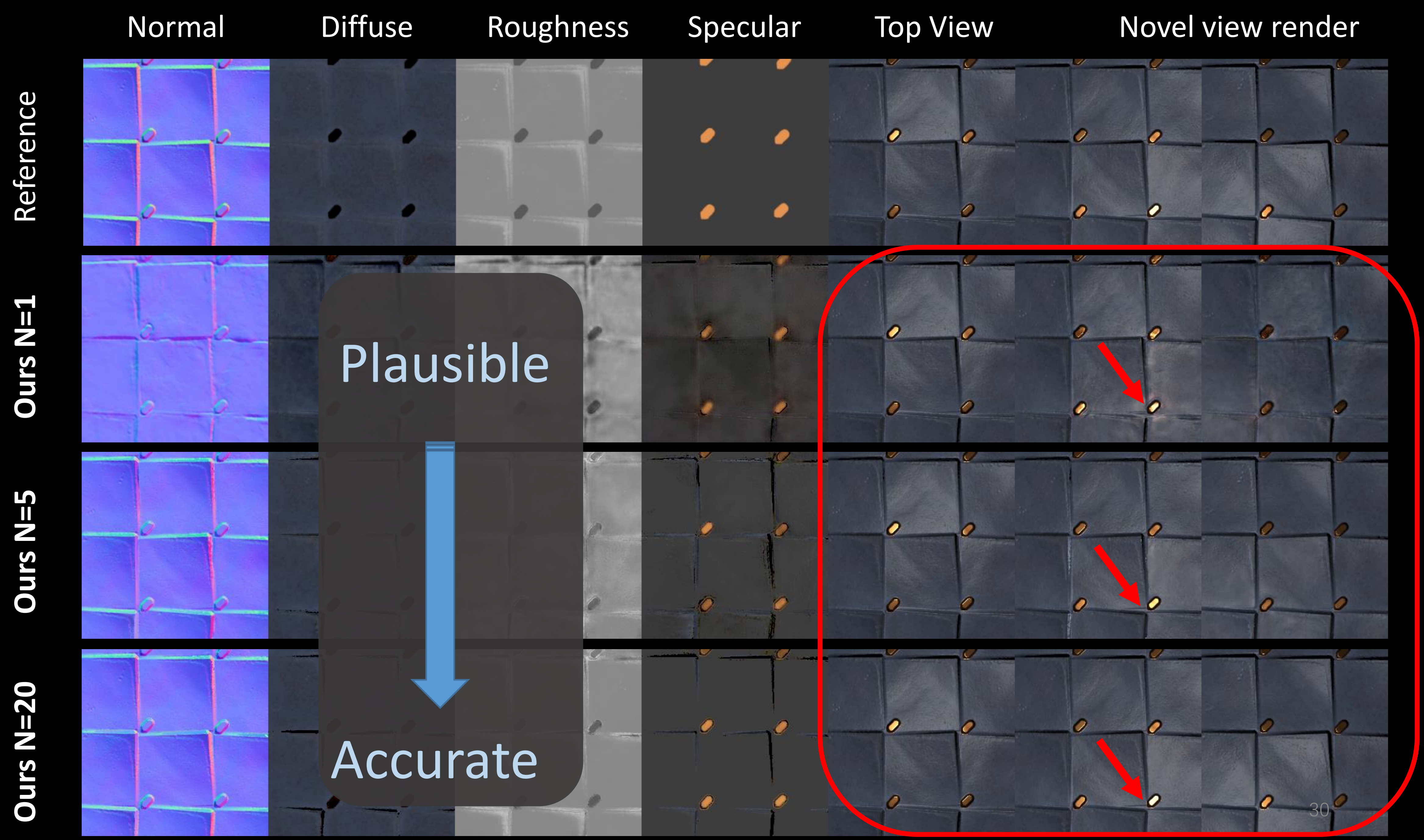


DETAIL REFINEMENT



IMPROVED QUALITY WITH SINGLE INPUT

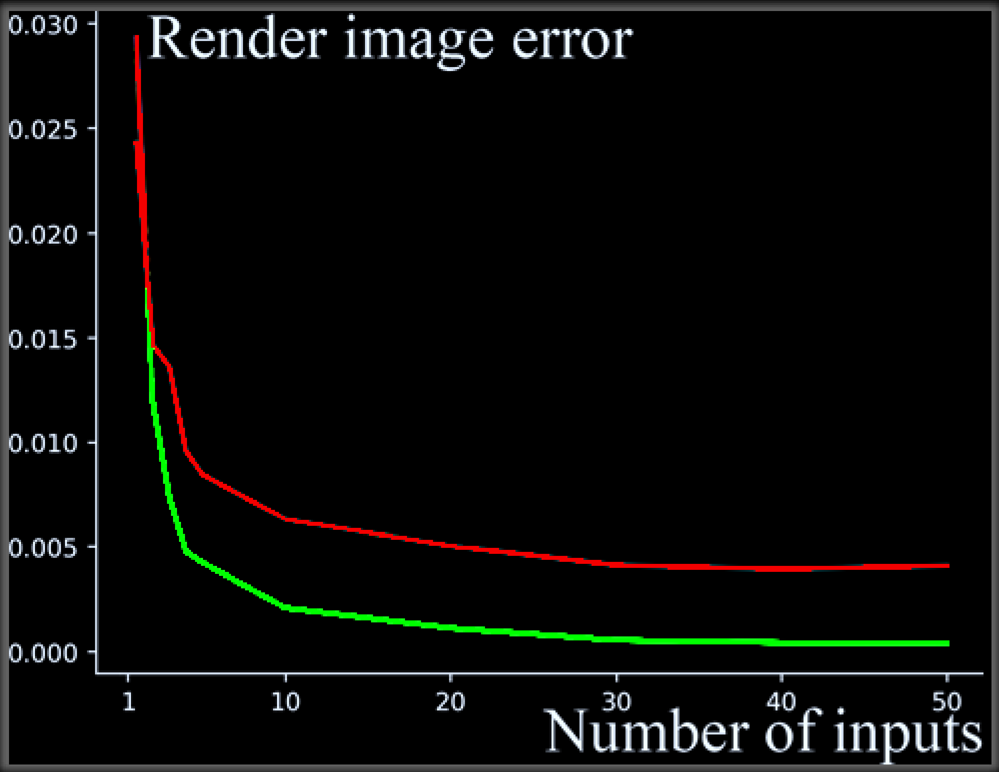


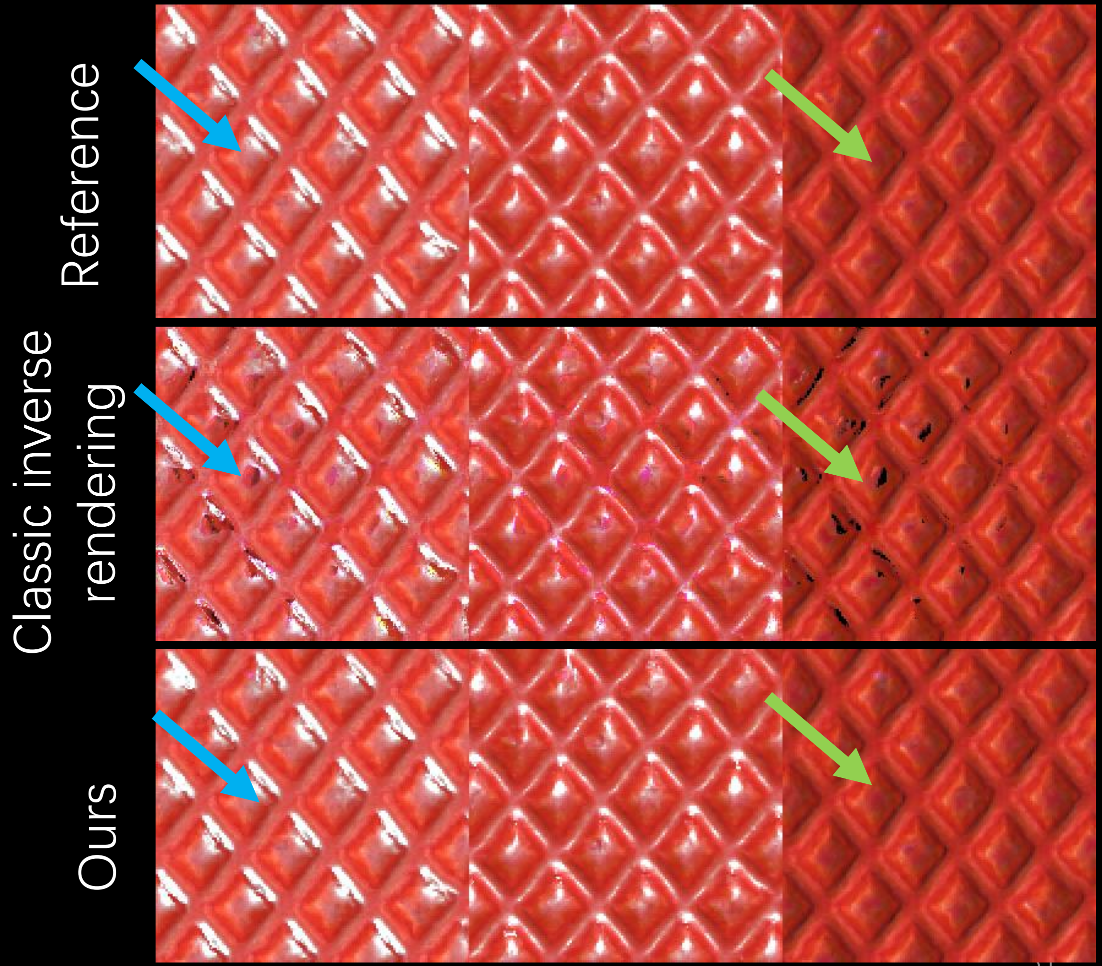


Normal
Diffuse
Roughness
Specular
Top View
Novel view render
Reference
Ours N=1
Ours N=5
Ours N=20
Plausible
Accurate

COMPARISON WITH CLASSIC INVERSE RENDERING

Classic inverse rendering ours





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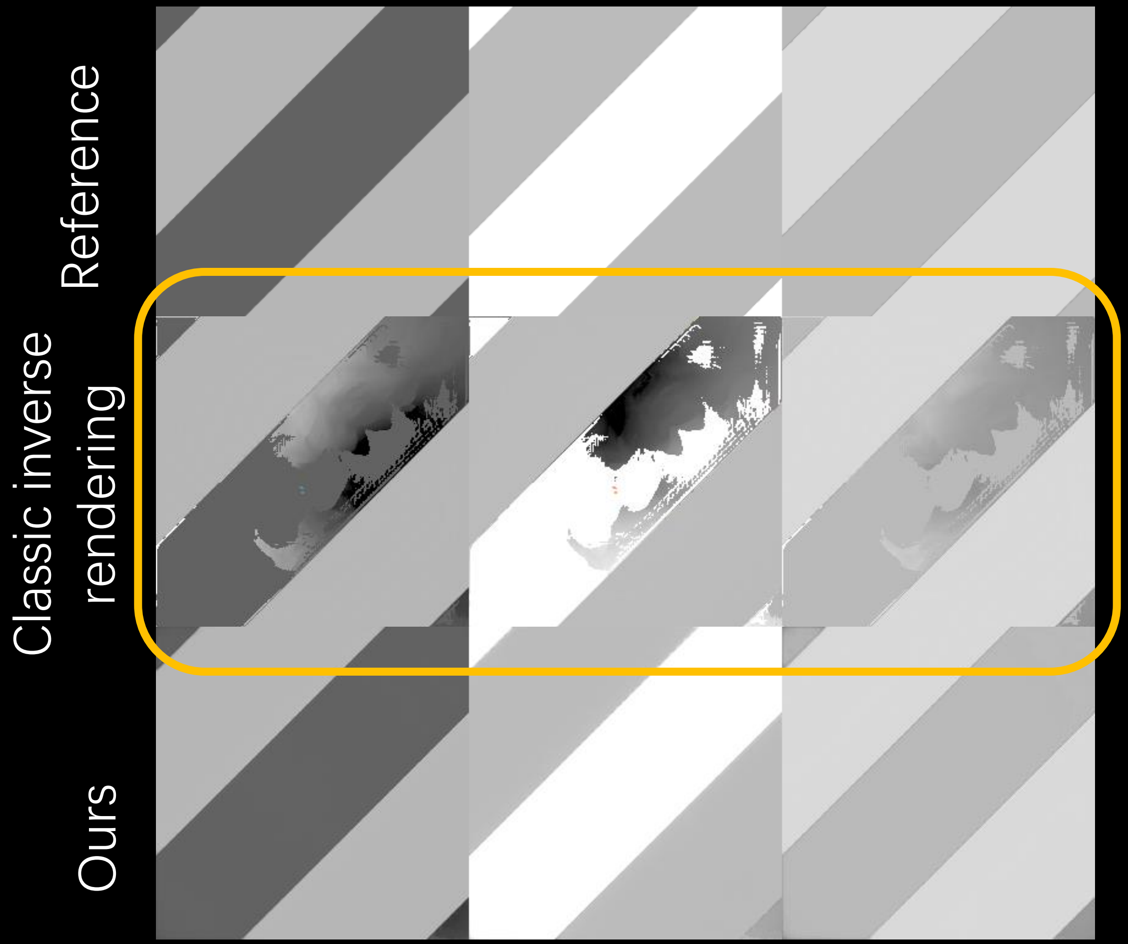
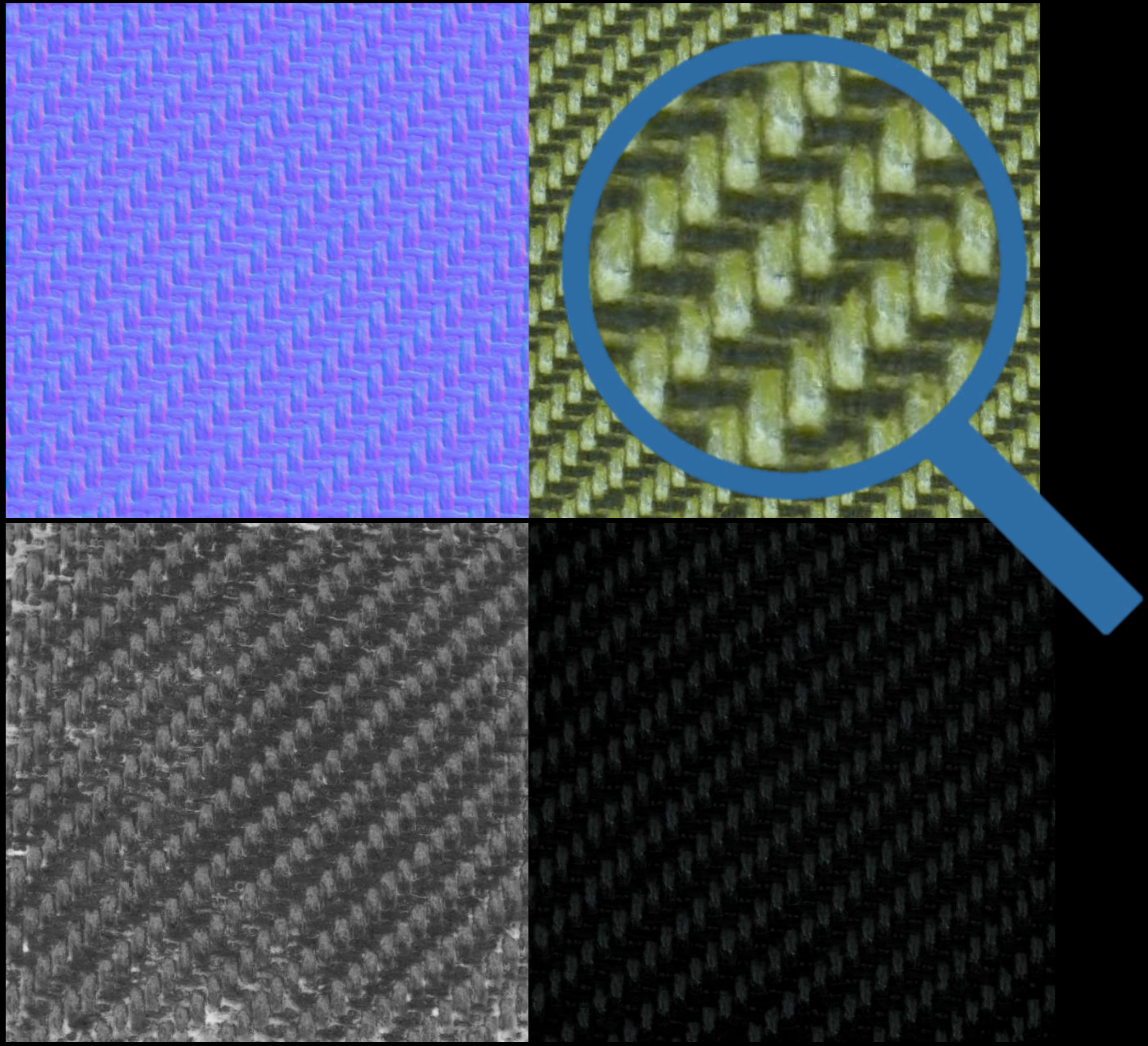
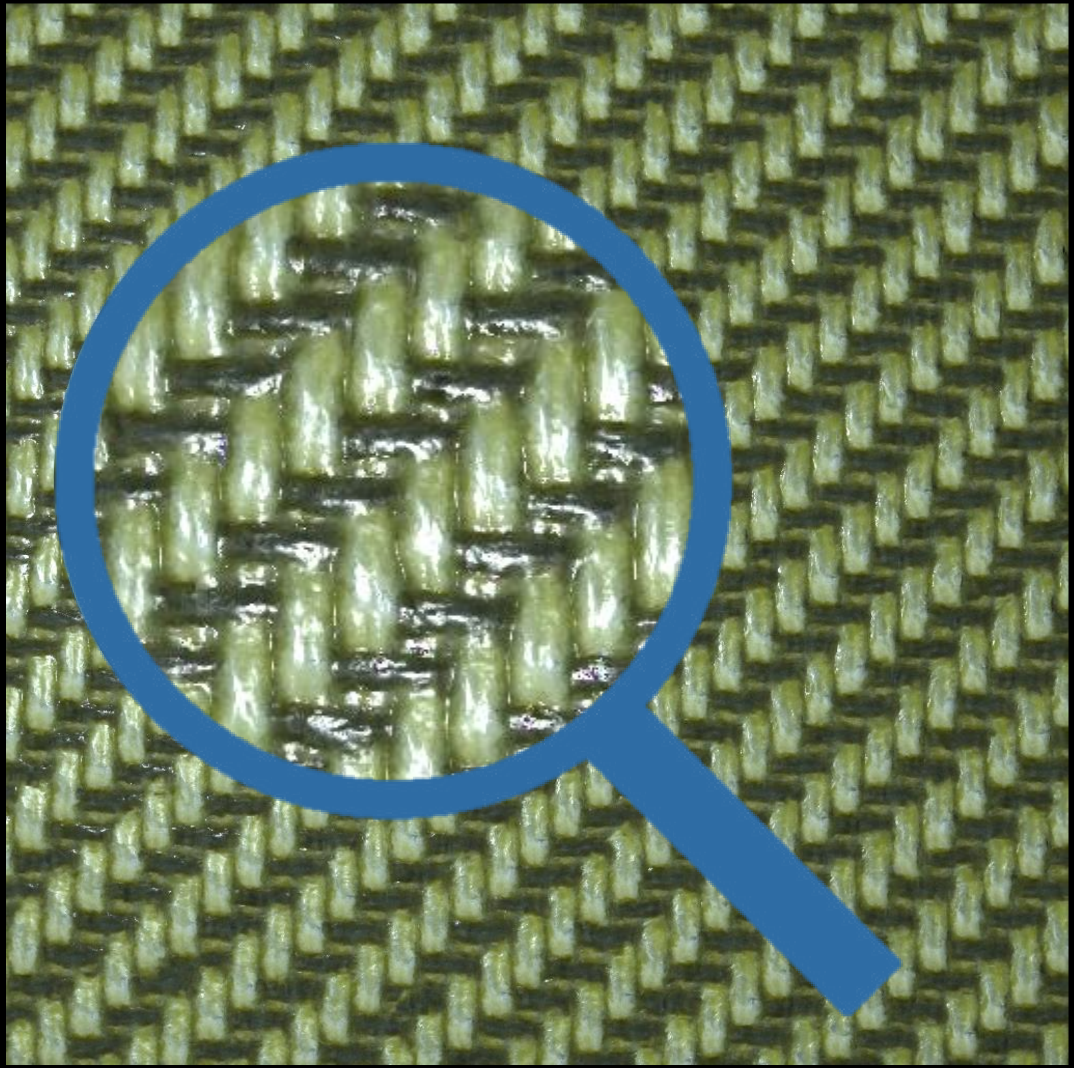


HIGH RESOLUTION RESULTS

Support arbitrary resolution!



Estimated SVBRDF with 20 input photos



Novel view rendering

HIGH RESOLUTION RESULTS

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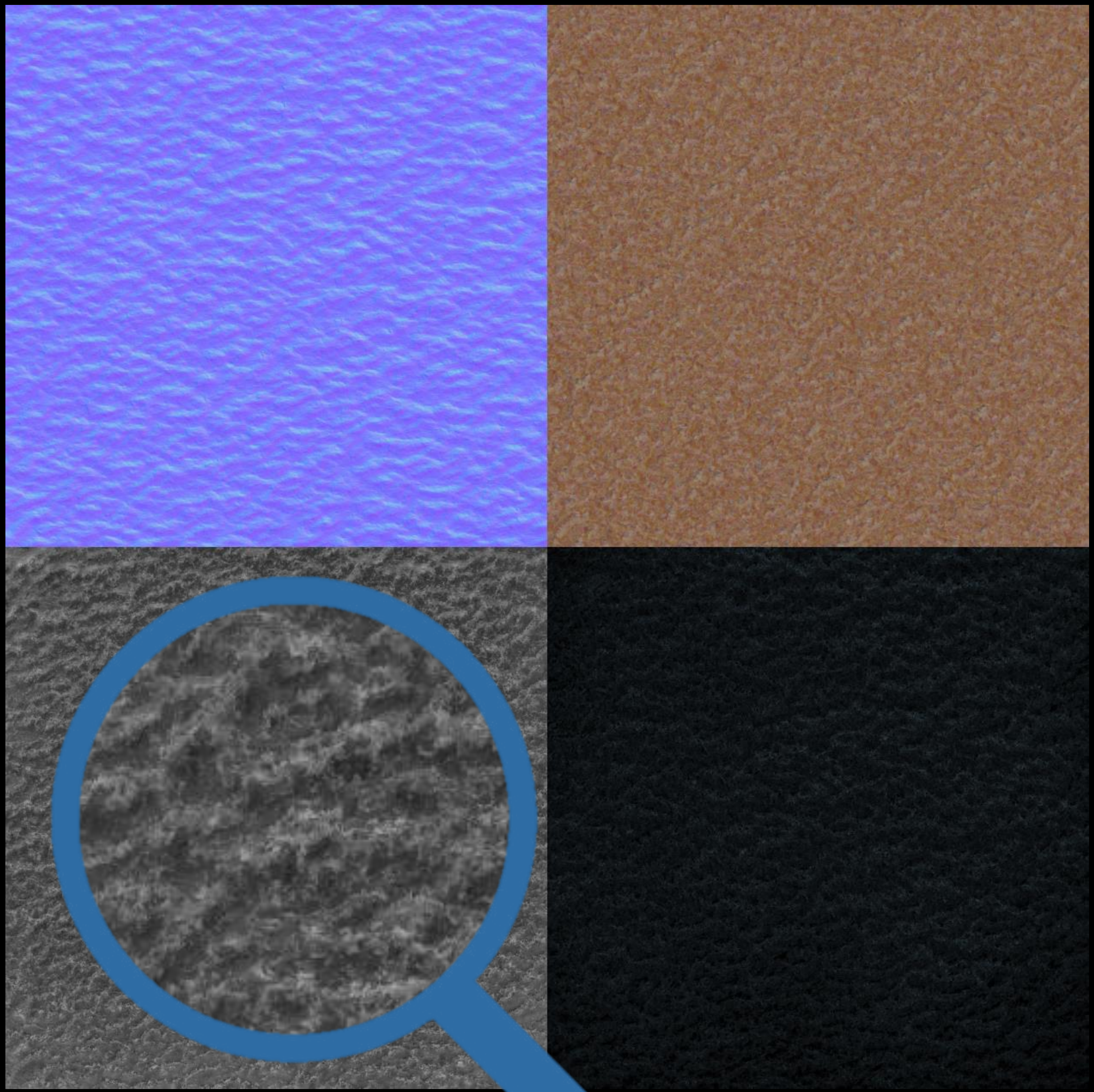

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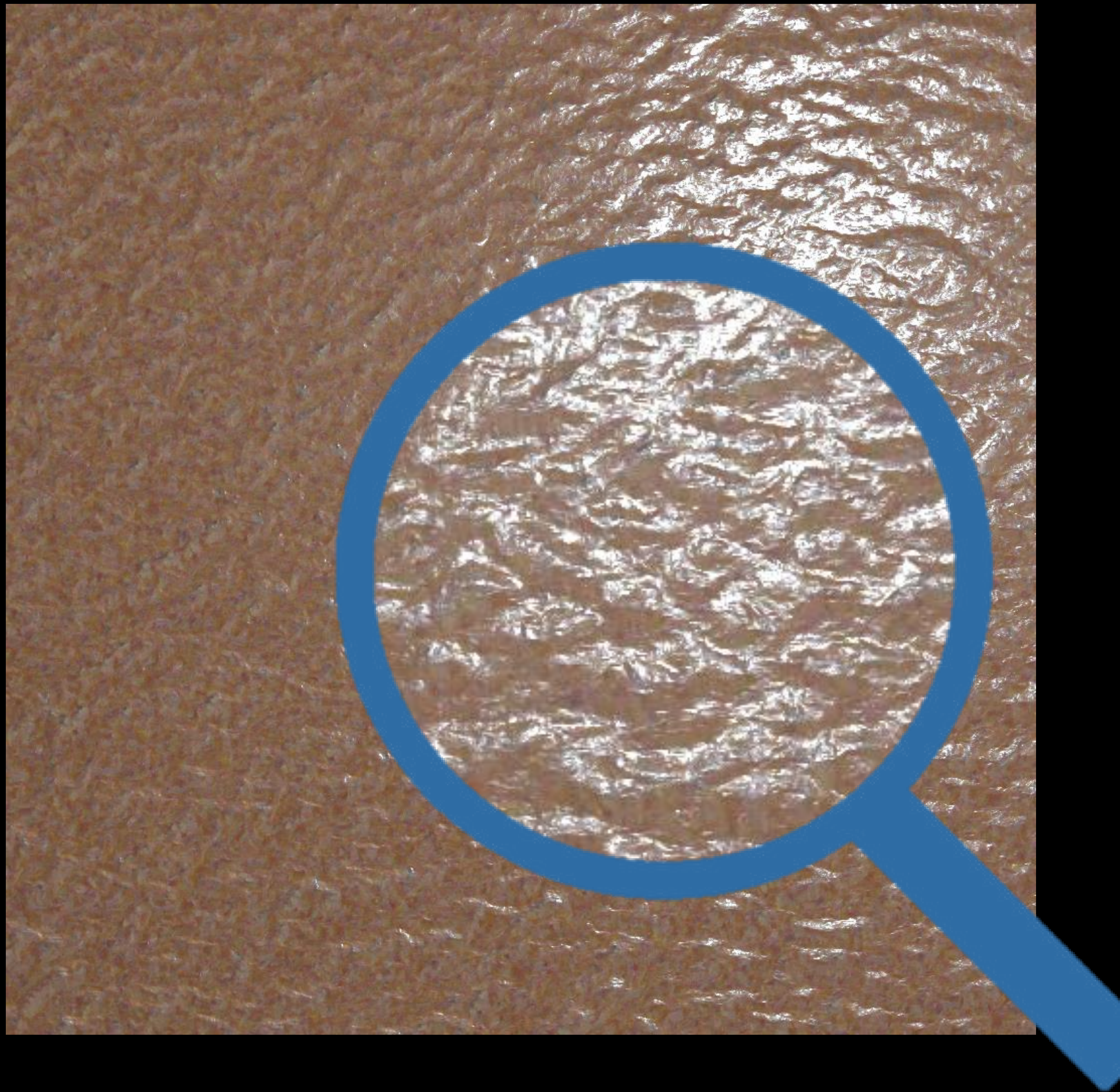

Novel view rendering

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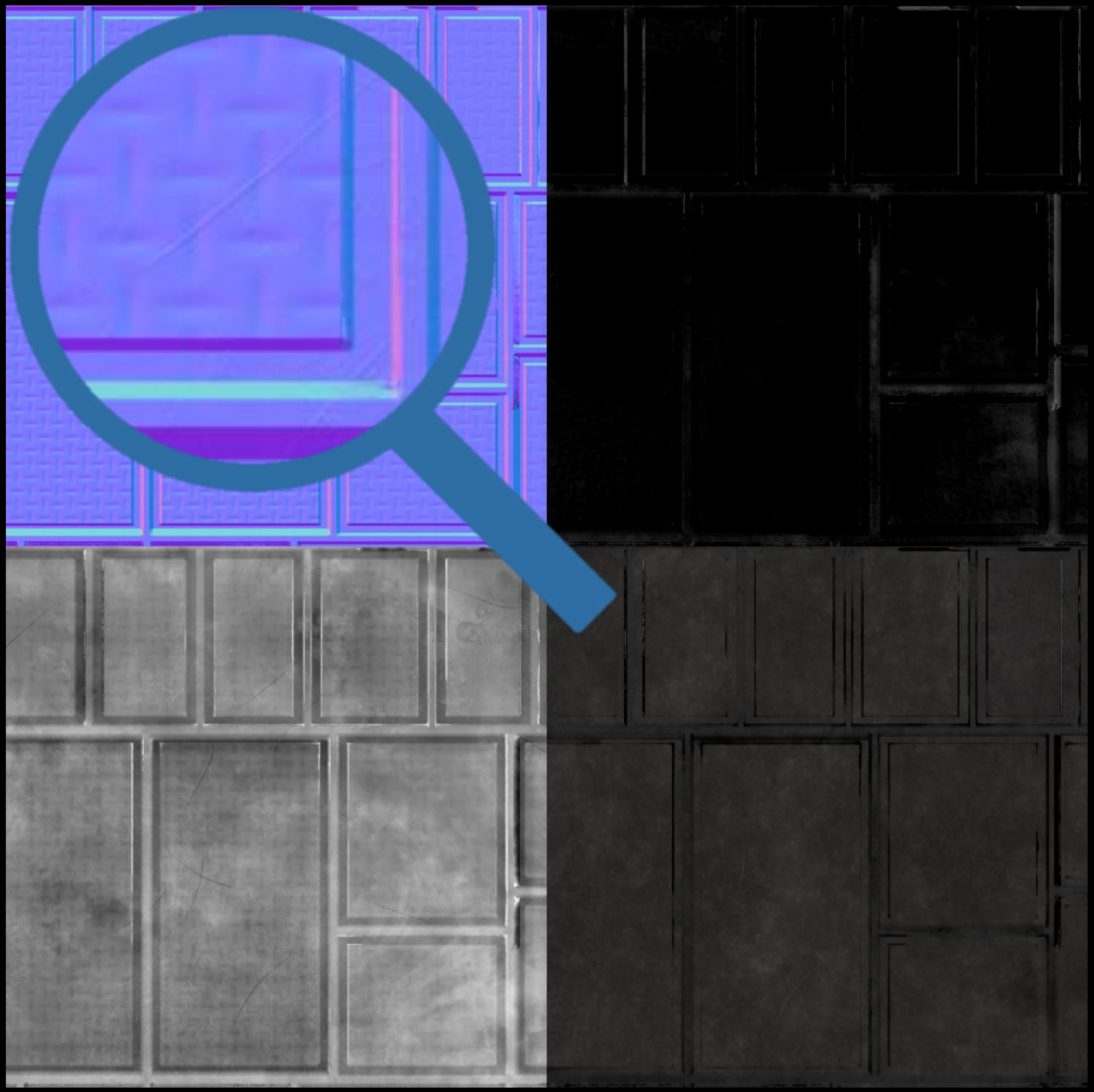
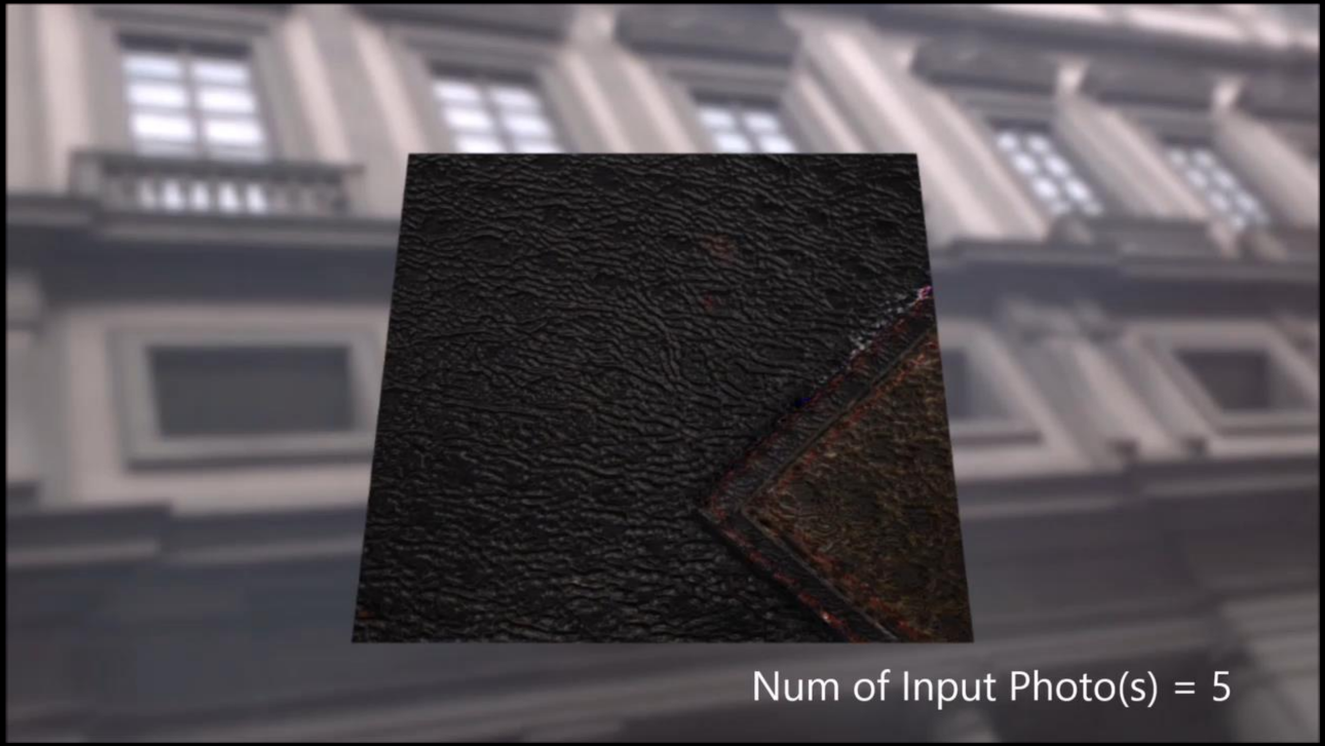


Estimated SVBRDF with 20 input photos

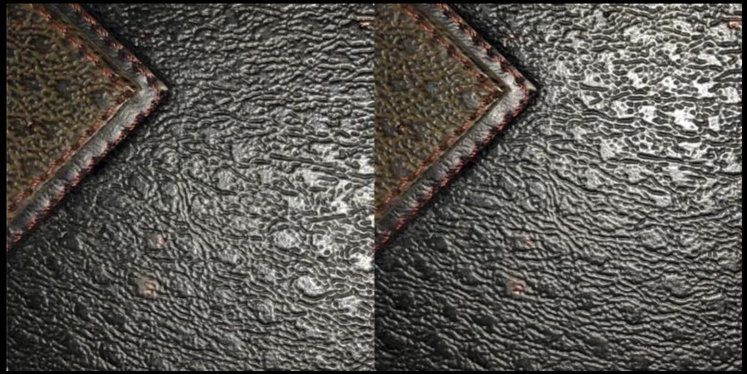
Novel view rendering

REAL CAPTURED RESULTS

Leather, 1k resolution, 5 input images

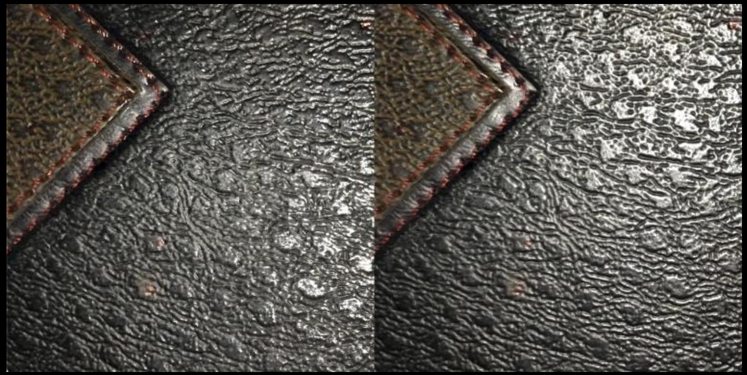


GT



N=1

N=5



Novel view

REAL CAPTURED RESULTS

Card, 1k resolution, 20 input images

GT

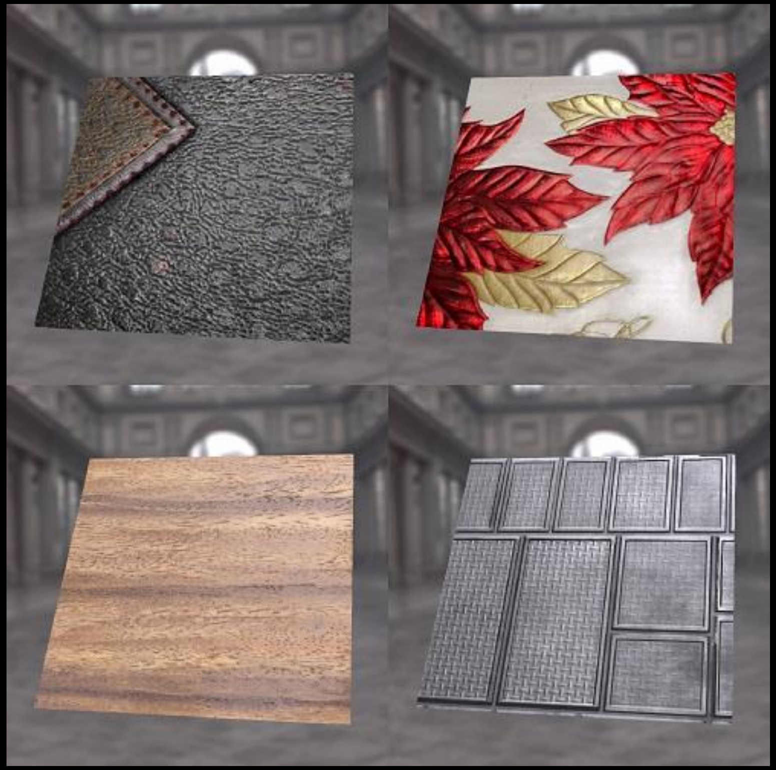
N=1

N=20

Novel view

CONCLUSION & FUTURE WORK

- A unified deep inverse rendering framework
  - Performs optimization in SVBRDF latent space
  - Handles arbitrary number of inputs
- Future Work
  - Leverage better initialization strategy
  - Geometry + appearance estimation



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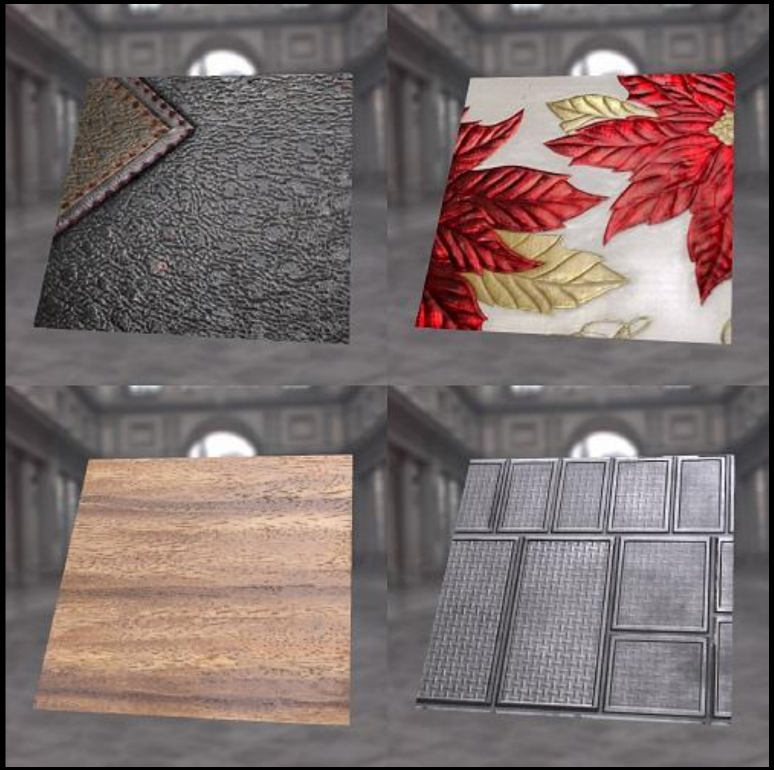
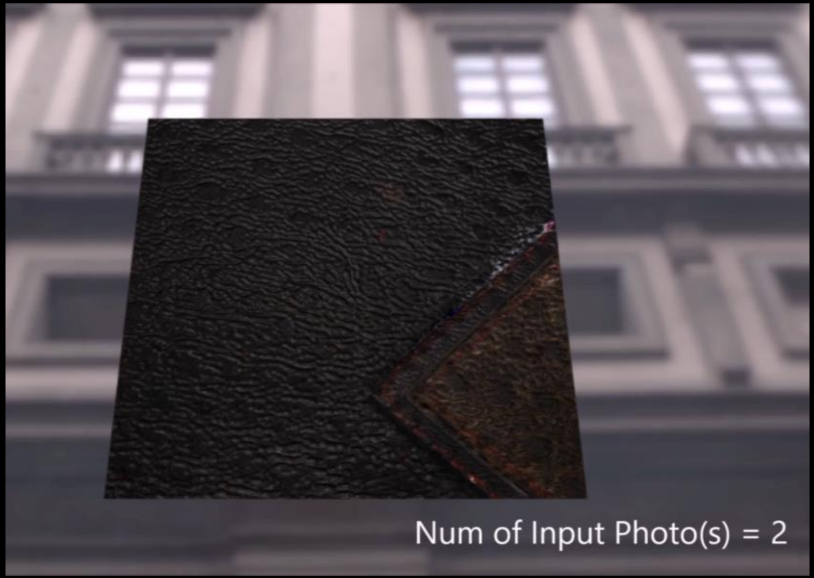
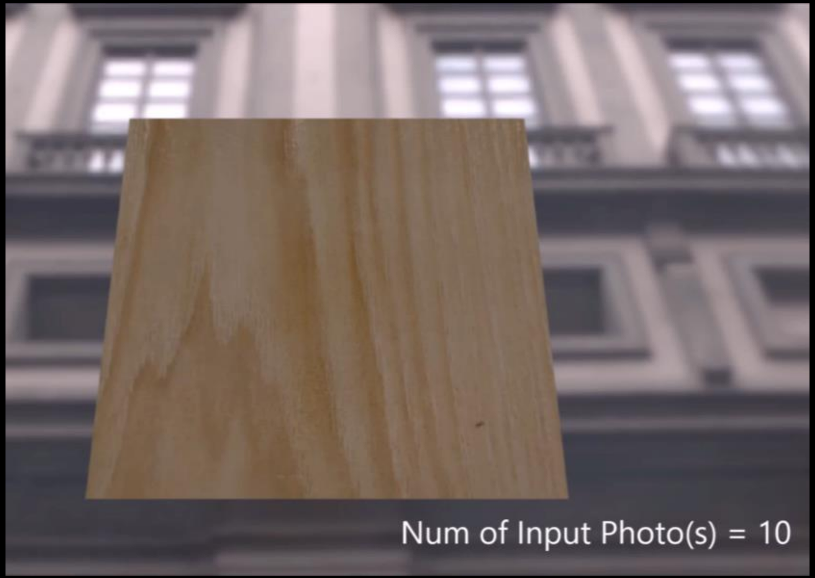


ACKNOWLEDGEMENTS

- Anonymous Reviewers
- Deep Materials dataset and model [Deschaintre et al. 2018]
- NSF grant IIS - 1350323
- National Natural Science Foundation of China


Num of Input Photo(s) = 2


Num of Input Photo(s) = 10


Num of Input Photo(s) = 20

Thanks