BRDF Estimation of Complex Materials with Nested Learning
- Supplementary material -

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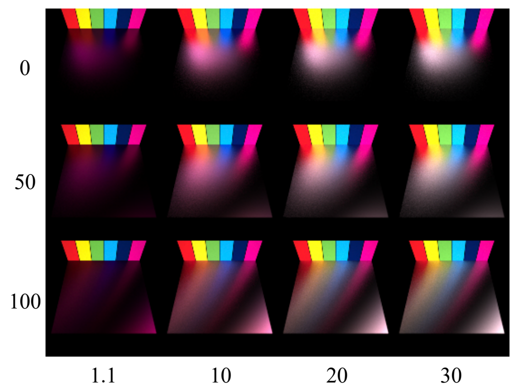

Figure 1: Anisotropy (y axis) and N_d (x axis) variations for fixed parameters of: roughness 20, pure red RGB_0, and pure blue RGB_{90}. Observe how increasing N_d (from left to right) reduces the effect of RGB_0 and RGB_{90} as more (white) light is reflected.

1. Dependency between parameters.

The definition of the BRDF model causes some dependencies between parameters. Figure 1, shows how increasing the value of N_d affects the influence of the albedo values in the final appearance. Materials with R (roughness) set to a high value are lambertian by definition, canceling the impact of all parameters but RGB_0.

In Figure 2 we can observe how the network has captured these dependencies. The accuracy for RGB_0 increases with roughness, as it has a greater influence in the appearance of the material (especially when roughness>90), while the opposite happens as expected, for RGB_{90} in the same range of values, when the specular component is minimal. Note that, when the material is very specular, the values of RGB_0 are irrelevant in the final appearance.

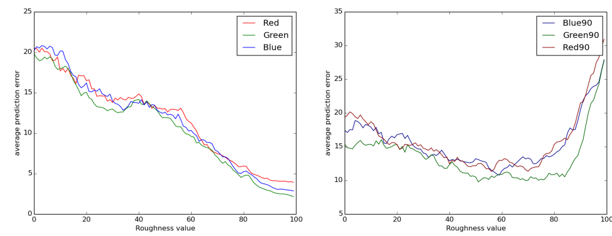

Figure 2: Average prediction error for different values of R of RGB_0 (left) and RGB_{90} (right).

2. Qualitative Evaluation on Synthetic Data

Figure 3 shows a qualitative evaluation of our method on the test set. We show random target materials and their corresponding prediction, rendered from the same viewpoint. For each target, we input to the network the 30° and 60° homographies and obtained a material prediction. This qualitative analysis confirms that our method can successfully capture complex reflectance behaviors.

We additionally tested the generalization of the predicted material to novel viewpoints. In Figure 4, we render the predicted material, computed using the two viewpoints highlighted in green, from the 14 viewpoints of our complete dataset. The pixel-wise visualization of the renders demonstrates how well the predicted material from just two views generalizes to new views.

3. Comparison with State of the Art [1]

In Figure 5 we qualitative compare our results with the results obtained by the method of Li *et al.* [1] in our synthetic test set. We want to remark that the significant differences between the two methods prevent to obtain conclusive comparisons. Li's method predicts a per-pixel simplified BRDF from a single image, which enables the computation of reflectance models of textured objects. In contrast, we obtain a unique BRDF for the entire material from two images, but ours is a richer model. For fairness, we only show

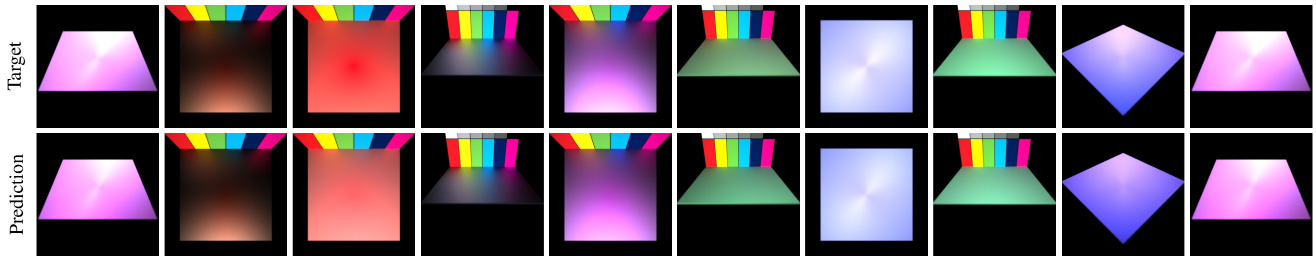

Figure 3: Qualitative evaluation on our synthetic test set. Although our network only needs the input of two views, we evaluate its performance using all of the 14 views.

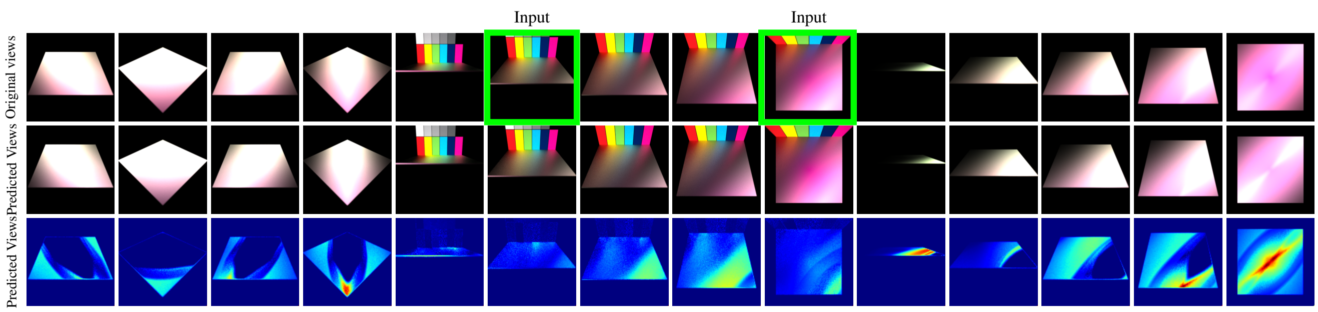

Figure 4: All 14 views of our dataset (top), our prediction (middle) and the L2 error per pixel (bottom). Note that we only use as a input the *homographied* views highlighted in green, the rest of original views are only showed to assess the generalization of the predicted material to new views.

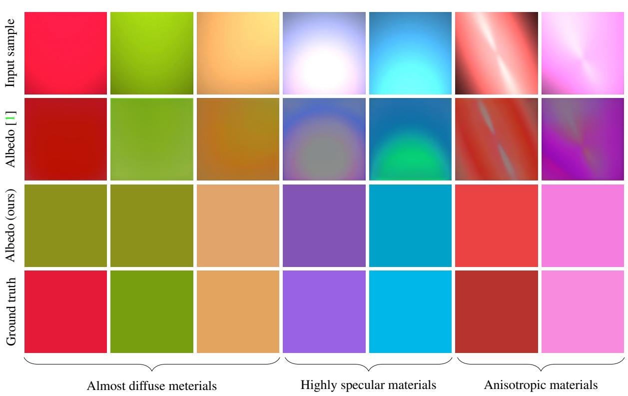

Figure 5: Qualitative comparison of our predicted albedo (RGB_0) and Li *et al.* [1] on our testset. Li's method handles well almost diffuse materials, but fails in computing the albedo in highly specular and anisotropic materials.

the results of the albedo predicted by Li and the RGB_0 of our model. Results show that Li's method can cope with our dataset when the material properties correspond to an almost diffuse material. In the case of highly specular materials or anisotropic materials, Li's method tends to merge the specular component into the albedo component. In contrast, our method effectively predicts the albedo in isolation.

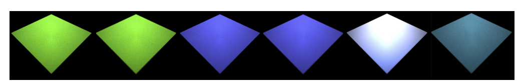

Figure 6: Pairs of target and matched images with SQP. The leftmost two pairs are Lambertian ($R = 100$), affected only by RGB_0 values. The rightmost pair has a roughness R value below 90.

4. Optimization Strategy

Following previous work [3] we performed an experiment: our goal was to fit the three RGB_0 albedo values of a diffuse material by means of a standard non-linear sequential quadratic programming solver (SQP) ([2]) with a pixel-wise least squares error function, comparing the target and the rendered image. In Figure 6 we can observe that, for a limited set of parameters, the results are compelling. However, the presence of an additional specular component, mostly white, biases the result of the RGB_0 parameters towards a desaturated value. As the number of parameters increased, the optimizer results became more unstable in our experiment, discouraging further exploration.

References

[1] X. Li, Y. Dong, P. Peers, and X. Tong. Modeling surface appearance from a single photograph using self-augmented con-

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[3] A. Ngan, F. Durand, and W. Matusik. Experimental analysis of brdf models. In *Proceedings of the Sixteenth Eurographics Conference on Rendering Techniques*, EGSR '05, pages 117–126, Aire-la-Ville, Switzerland, Switzerland, 2005. Eurographics Association. 2