Real-time Multi-material Reflectance Reconstruction for Large-scale Scenes under Uncontrolled Illumination from RGB-D Image Sequences -Supplementary Material-

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In the scope of this supplementary material, we provide additional results and information about the evaluation of our pipeline. First, we compare our approach to the sole use of the HemiCNN in order to assess the gain in quality of the reconstructed materials induced by our improvements. Afterwards, we provide information about the synthetic test scene setup and show additional visual as well as quantitative results for a large number of synthesized scenes using various different combinations of material and geometry.

In the following quantitative error plots, we average $L_1$ errors over the pixels of each frame. We mask out pixels for which our reconstruction does not provide any estimates to avoid distorting the averaged errors by gaps in the reconstruction.

1. Further Results on Synthetic Scenes

The general setup of our synthetically generated test scenes is depicted in Figure 1: A camera oscillates up and down while moving around one or more objects and being directed to the scene’s center. An approximation of an environment map consisting of 32 directional lights is used to illuminate the scenes. The environment map itself can be seen in Figure 2.

For further testing, we generated additional test scenes by applying 43 different scanned fabric materials to two different meshes, each resulting in a total of 86 scenes. The fabrics are selected from a database of anisotropic Ward SVBRDFs [2]. For each material, we average their specular albedo and lobe roughness parameter maps to match our homogeneous, isotropic model. Since, however, these fabrics contain a broader range of values than the SynBRDF dataset, the HemiCNN is not able to reconstruct all materials sufficiently due to a lack of such samples during its training. Figure 3 shows that all reconstructed $\alpha$ values fall into a small corridor between 0.1 and 0.21.

Figures 4 and 5 depict exemplary results of our recon-
Construction pipeline. In all cases, the spatially varying details in the diffuse albedo are conserved by the reconstruction. Our pipeline overestimates the roughness of the first example, which can be explained by such small $\alpha$ values being underrepresented in the HemiCNN’s training data.

In Figure 6 we show quantitative errors computed on different subsets of the 86 synthetic test scenes. Splitting the scenes according to their roughness, we see that our pipeline performs well for $\alpha$ values that are abundant in the HemiCNN’s training set (“$\alpha$ within training bounds”).
When reconstructing material characteristics with $\alpha$ being outside of the range $[0.1, 0.21]$, the estimates for $\kappa_s$ and $\alpha$ are significantly worse (“$\alpha$ lower / higher than training bounds”). Due to the nature of the albedo refinement process, this error propagates into $\kappa_d$ as well. Furthermore, we see in the bottom right graph of the figure (“all materials”) that the albedo refinement systematically decreases the error over the diffuse albedo and the rendered RGB values.
2. Comparison to HemiCNN

In addition to the qualitative results already shown in the paper, Figure 7 provides a quantitative comparison of the results obtained using HemiCNN as proposed by Kim et al. [1]. HemiCNN with our minor changes regarding the loss function, as well as projection used to generate the hemi images, and our complete pipeline including the albedo refinement. Since HemiCNN by design only estimates a single material in the scene, we combine it with our multi-material framework in order to get comparable results. While we use ground truth lighting and ground truth segmentation available for the synthetic cubes and bunnies scenes, we apply a segmentation and lighting estimation for the reconstruction and re-rendering as described in the accompanying paper.

The main paper already shows that the spatially varying reflectance characteristics, reconstructed using our albedo refinement, add a significant amount of realism to scenes containing inhomogeneous materials (e.g. the bunnies and the office scenes). Additionally, Figure 7 shows that our modified HemiCNN is able to estimate the specular material parameters more accurately.

3. Additional Real-world Results

Figure 8 shows a few frames of another real-world scene (teapot) captured using the Microsoft Kinect v2 and the corresponding renderings. The lighting estimation does not have to be repeated as we use the same office room and the different objects do not have a significant influence on the point light approximation of the illumination.

The office and teapot scenes’ reflectance reconstruction can be seen in the attached video.

References

Figure 7. Evaluation of our method against the one of Kim et al. [1] by comparing L1 errors of the re-rendered RGB images over the frames.

Figure 8. Three frames of a second real-world scene (teapot) captured with the Microsoft Kinect v2 sensor. The columns show (from left to right) the input RGB images, the refined diffuse albedos as calculated by our pipeline, and renderings of the captured scene using the estimated geometry, illumination and reflectance characteristics.