Deep image-based Adaptive BRDF Measure

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Abstract

Efficient and accurate measurement of the bi-directional reflectance distribution function (BRDF) plays a key role in realistic image rendering. However, obtaining the reflectance properties of a material is both time-consuming and challenging. This paper presents a novel iterative method for minimizing the number of samples required for high quality BRDF capture using a gonio-reflectometer setup. The method is a two- step approach, where the first step takes an image of the physical material as input and uses a lightweight neural network to estimate the parameters of an analytic BRDF model. The second step adaptive sample the measurements using the estimated BRDF model and an image loss to maximize the BRDF representation accuracy. This approach significantly accelerates the measurement process while maintaining a high level of accuracy and fidelity in the BRDF representation.

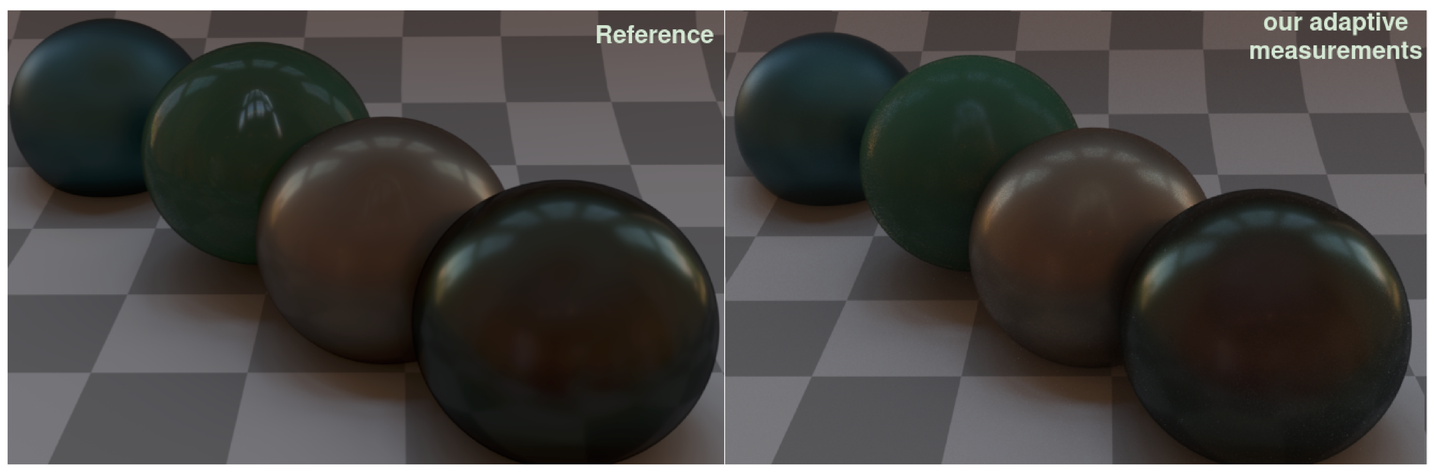

Figure 1: Rendered balls with our BRDF adaptive Measurements VS ground truth

We present a novel solution for BRDF measurement with the following key contributions:

- **Lightweight**: Our approach utilizes images to learn priors, eliminating the need for complex measurement procedures. This significantly streamlines the measurement process and establishes an end-to-end pipeline;
- **Adaptive and Accuracy**: Experimental results demonstrate that our image-based adaptive method effectively measure a wide range of materials. Its adaptability leads to highly accurate rendered results for each material,outperforming previous methods at some aspects.

Approach

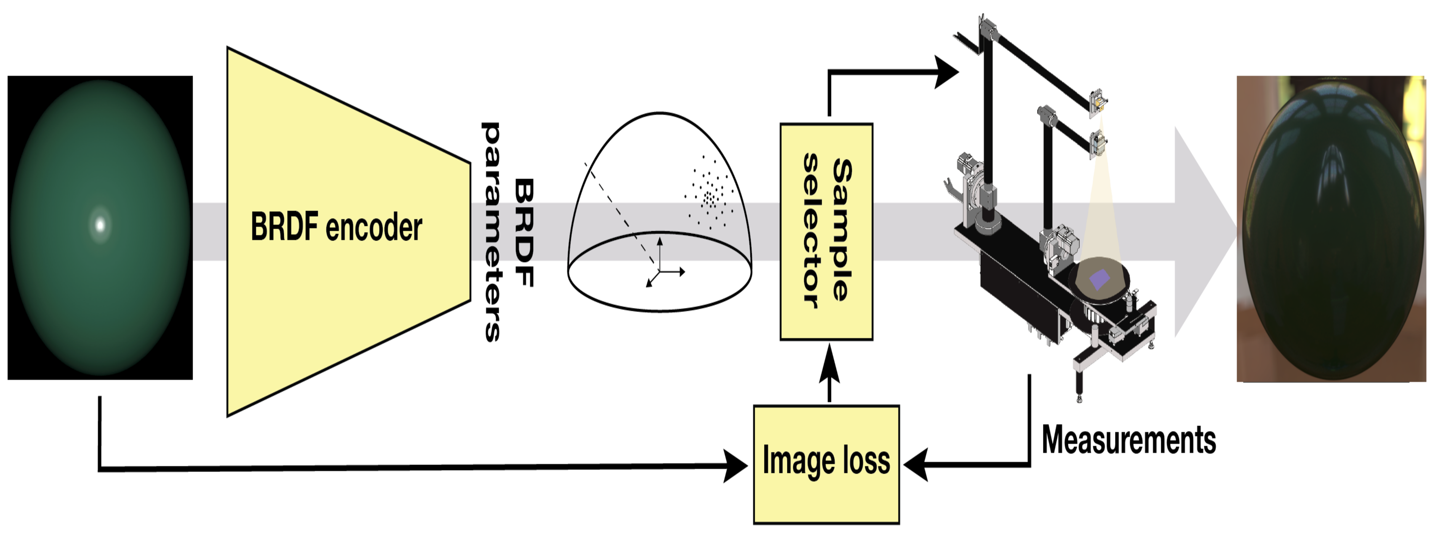

Figure 2: Method Flowchart of Deep Image-based Adaptive Reflectance Measure. For a fixed material, we use its image as input to an encoder network, which then estimates the BRDF parameters for it. An adaptive sampler use these parameters to determine the outgoing direction locations. Finally, we progressively increase the number of these locations to achieve the minimum number of samples required while maintaining high fidelity.

BRDF Estimation

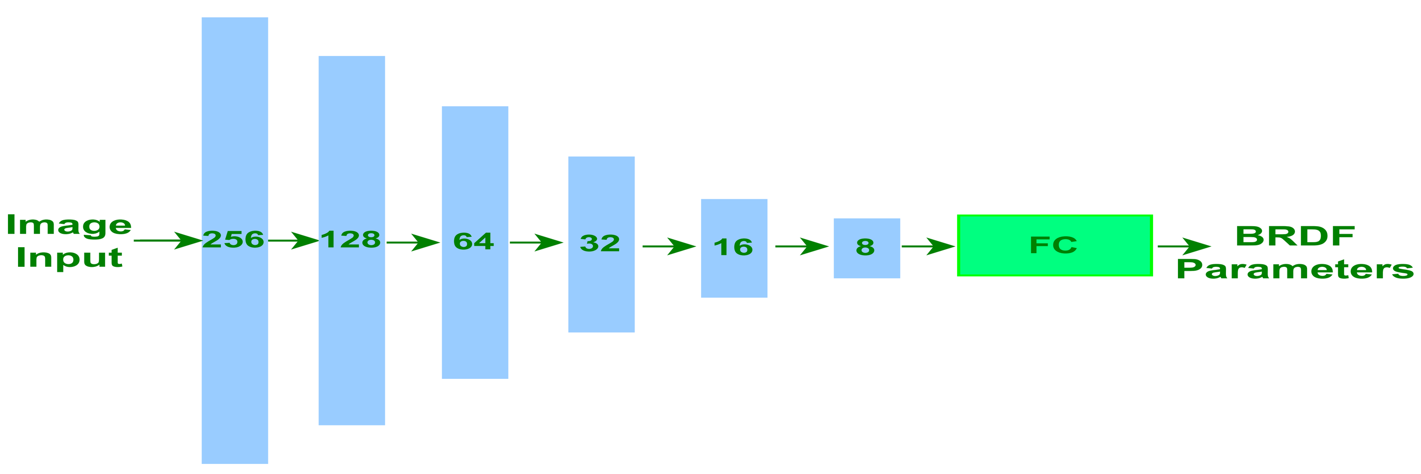

Figure 3: illustration of the encoder network architecture used for estimating BRDF parameters. Blue boxes denote convolutional layers with batch normalization and ReLU activation functions. The dimensions of these layers are the numbers inside them. The green box represents a fully con- nected layer outputting the BRDF parameters.

Adaptive Reflectance Sampling

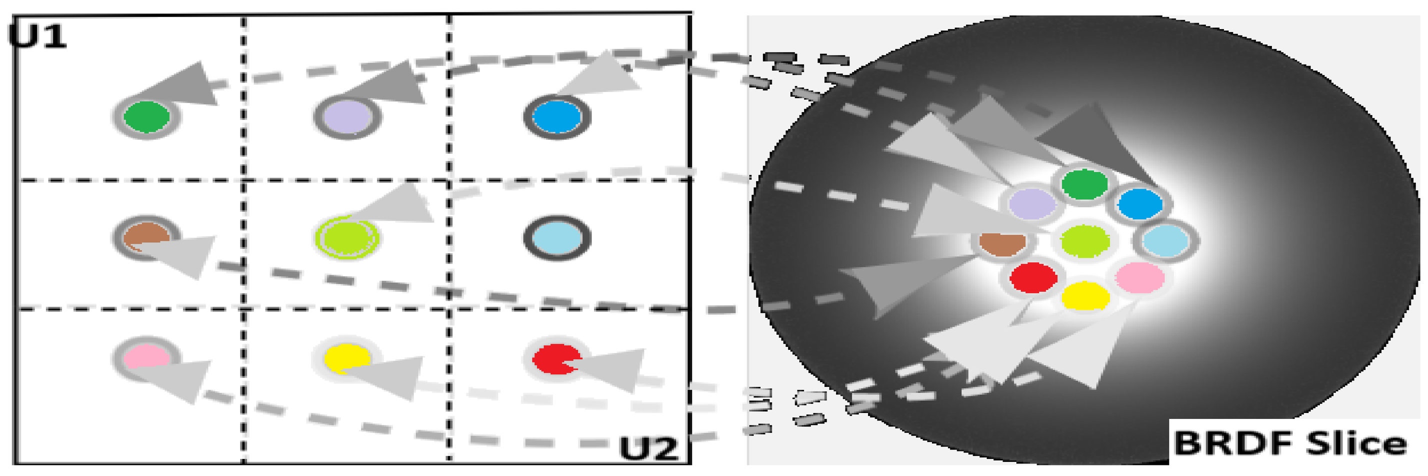

Figure 4: A visualization of the process g in Eq. **??** to calculate the adaptive sampler's position. We start by getting sample points (u_1, u_2) on a uniform grid in the unit square $[0, 1]^2$. The importance sampling process takes a sample point (u_1, u_2), and maps it to position on a 2D BRDF slice,and reverse wise works by its inverse function.

Results

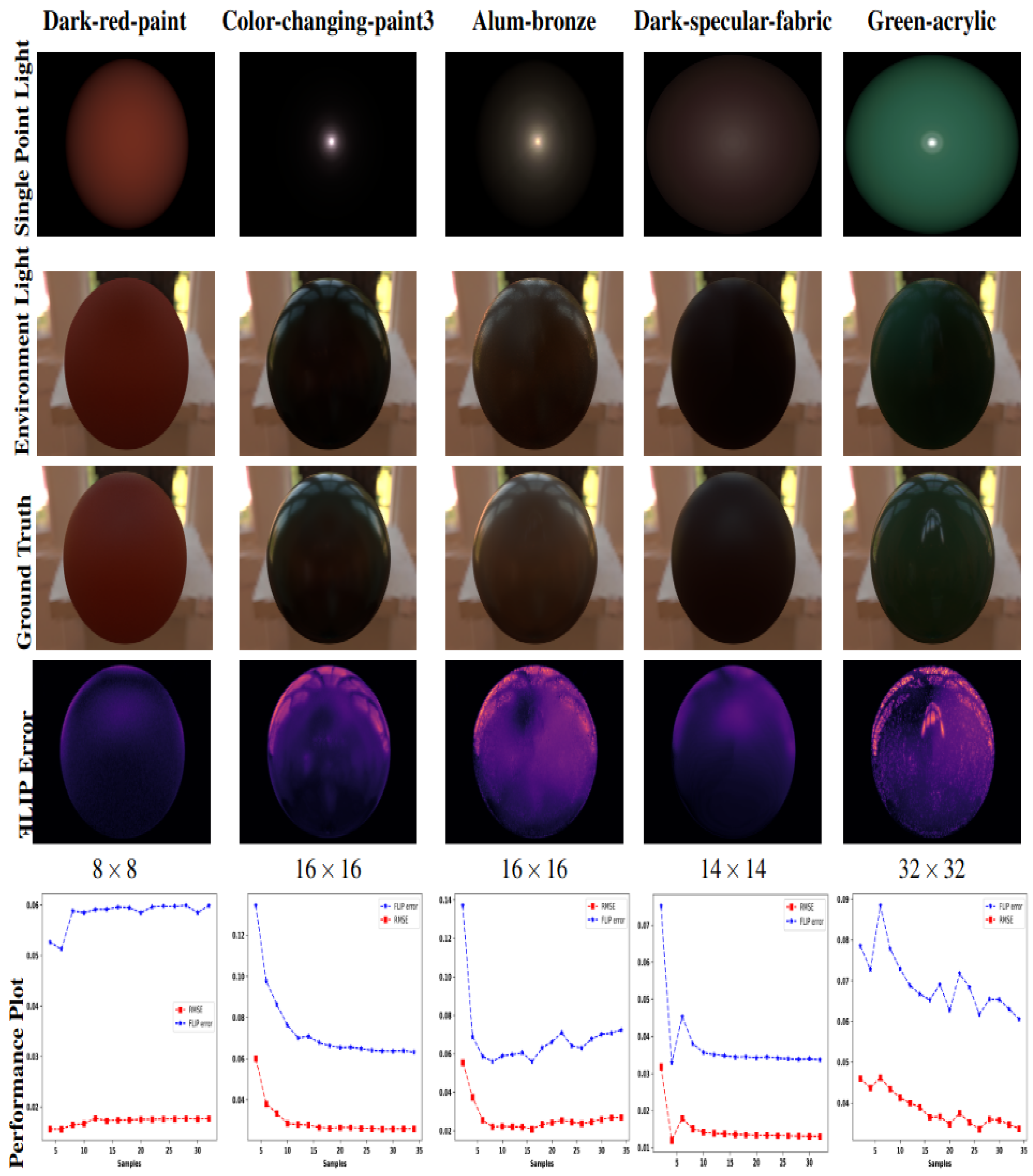

Figure 5: Rendered sphere of Five Different Materials from the MERL Dataset.The first row shows our measurements rendered under single-point lighting. The second row shows our measurements rendered under environmental lighting. The third row shows the ground truth rendered under the same environmental lighting conditions. The fourth row shows the ꟻLIP error images between the second and third rows. The final row presents a plot of error metric values versus the number of samples for each material. The Y-axis of final row represents the RMSE and ꟻLIP error values, while the X-axis indicates the sample counts, ranging from 2×2 to 32×32 of outgoing directions.

Conclusions

- We propose an image-based adaptive BRDF sampling method that significantly reduces BRDF measurement time while maintaining high accuracy and fidelity.
- We use a lightweight neural network and show that it can accurately estimate BRDF parameters and that this, in turn, can be used to importance sampling new directions for taking measurements.
- We validate our approach using both the MERL dataset and the Ward BRDF model.