



A Sparse Non-parametric BRDF model

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Introduction

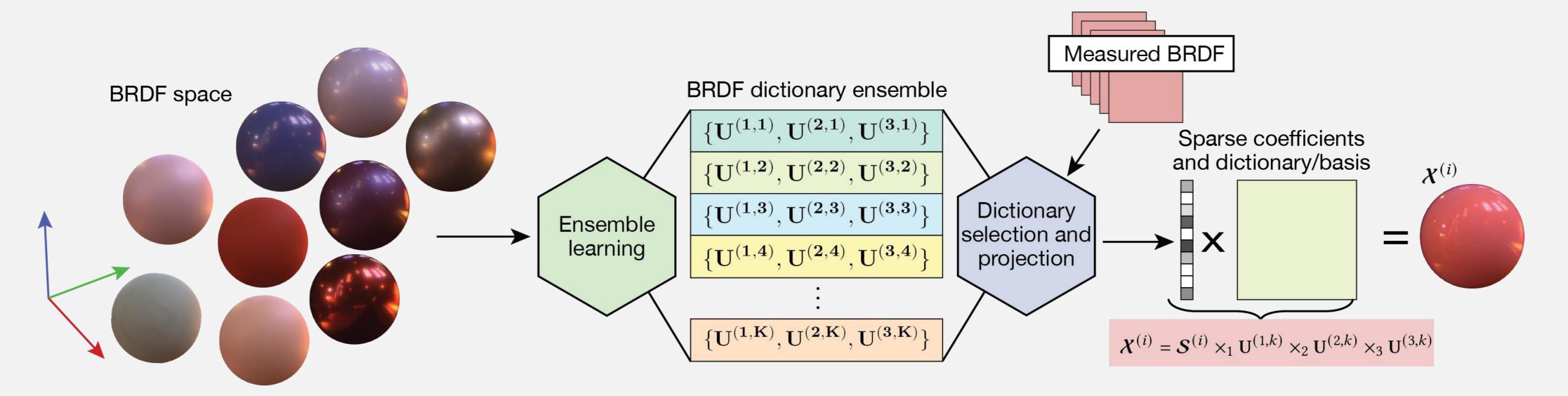
We present a sparse non-parametric Bidirectional Reflectance Distribution Function (BRDF) model. We use a dictionary learning approach and train a model capable of representing the space of possible BRDFs using a set of multidimensional sub-spaces, or dictionaries. By training the dictionaries under a sparsity constraint, the model guarantees high-quality representations with minimal storage requirements and an inherent clustering of the BDRF-space. The model can be trained once and then reused to represent a wide variety of measured BRDFs. In addition, we show that any two, or more, BRDFs can be smoothly interpolated in the coefficient space of the model rather than the significantly higher-dimensional BRDF space. Experimental results show that the proposed approach results in about 9.75dB higher signal-to-noise ratio on average for rendered images as compared to current state-of-the-art models.

Method

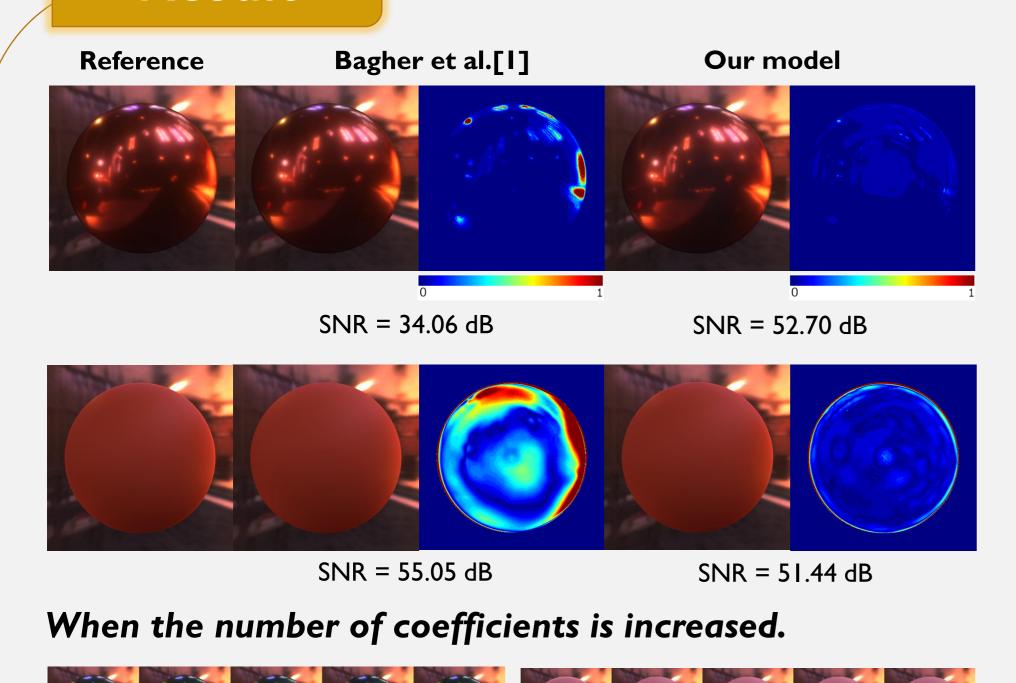
Our method consists of three following processes.

- I. Data Preprocessing $\rho_{t1} = \log(\rho(\omega_h, \omega_d) + 1)$, and $\rho_{t2} = \log(\rho(\omega_h, \omega_d) \cos Map + 1)$.
- 2. Ensemble Learning We train an ensemble of dictionaries $\{U^{(1,k)}, U^{(2,k)}, U^{(3,k)}\}_{k=1}^{K}$.
- 3. BRDF Model Selection Each BRDF is represented by $\chi^{(i)} = S^{(i)} \times_1 U^{(1,k)} \times_2 U^{(2,k)} \times_3 U^{(3,k)}$. Gamma-mapped MSE is applied as an error metric to perform a model selection on the BRDF-value domain.

BRDF interpolation on the learned dictionaries in the ensemble are smooth and orthogonal, which enables BRDF interpolation between two or more BRDFs in coefficient space.



Result



Evaluation with non-parametric BRDF models

BRDF Model	Average SNR (dB)	Standard deviation	Maximum SNR (dB)
Ours	52.5 I	4.975	62.16
Bagher et al. [1]	42.76	11.632	63.88
Bilgili et al. [2]	32.63	5.872	43.17
Tongbuasirilai et al. [3]	33.83	5.523	42.71

BRDF Interpolation



Reference

[2] Ahmet Bilgili, Aydn Öztürk, and Murat Kurt. 2011. A general BRDF representation based on tensor decomposition. Comput. Graph. Forum 30, 8 (2011), 2427–2439.

[3] Tanaboon Tongbuasirilai, Jonas Unger, Joel Kronander, and Murat Kurt. 2019. Compact and intuitive data-driven BRDF models. Visual Comput., 36, May 2019.