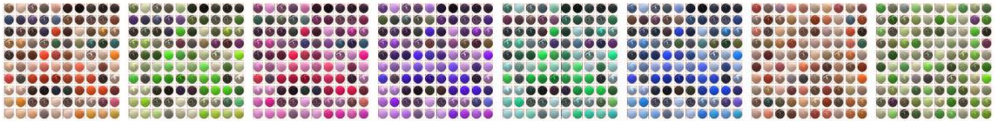
FreNBRDF: A Frequency-Rectified Neural Material Representation



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Introduction and Motivation

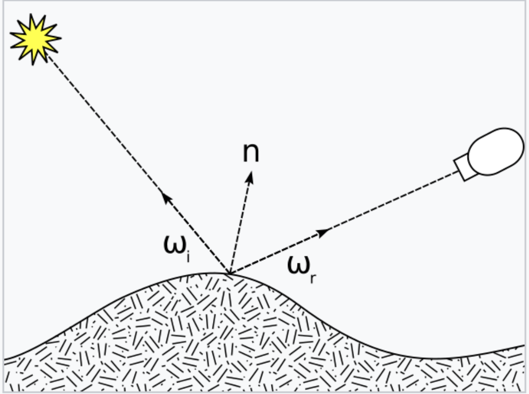

Diagram showing vectors used to define the BRDF. All vectors are unit length. ω_{i} points toward the light source. ω_{r} points toward the viewer (camera). n is the surface normal.

The rendering equations:

$$L_{\mathrm{o}}(\mathbf{x}, \omega_{\mathrm{o}}, \lambda, t) = L_{\mathrm{e}}(\mathbf{x}, \omega_{\mathrm{o}}, \lambda, t) + L_{\mathrm{r}}(\mathbf{x}, \omega_{\mathrm{o}}, \lambda, t)$$

$$L_{\mathrm{r}}(\mathbf{x}, \omega_{\mathrm{o}}, \lambda, t) = \int_{\Omega} f_{\mathrm{r}}(\mathbf{x}, \omega_{\mathrm{i}}, \omega_{\mathrm{o}}, \lambda, t) L_{\mathrm{i}}(\mathbf{x}, \omega_{\mathrm{i}}, \lambda, t)(\omega_{\mathrm{i}} \cdot \mathbf{n}) \, \mathrm{d}\, \omega_{\mathrm{i}}$$

https://en.wikipedia.org/wiki/Bidirectional_reflectance_distribution_function

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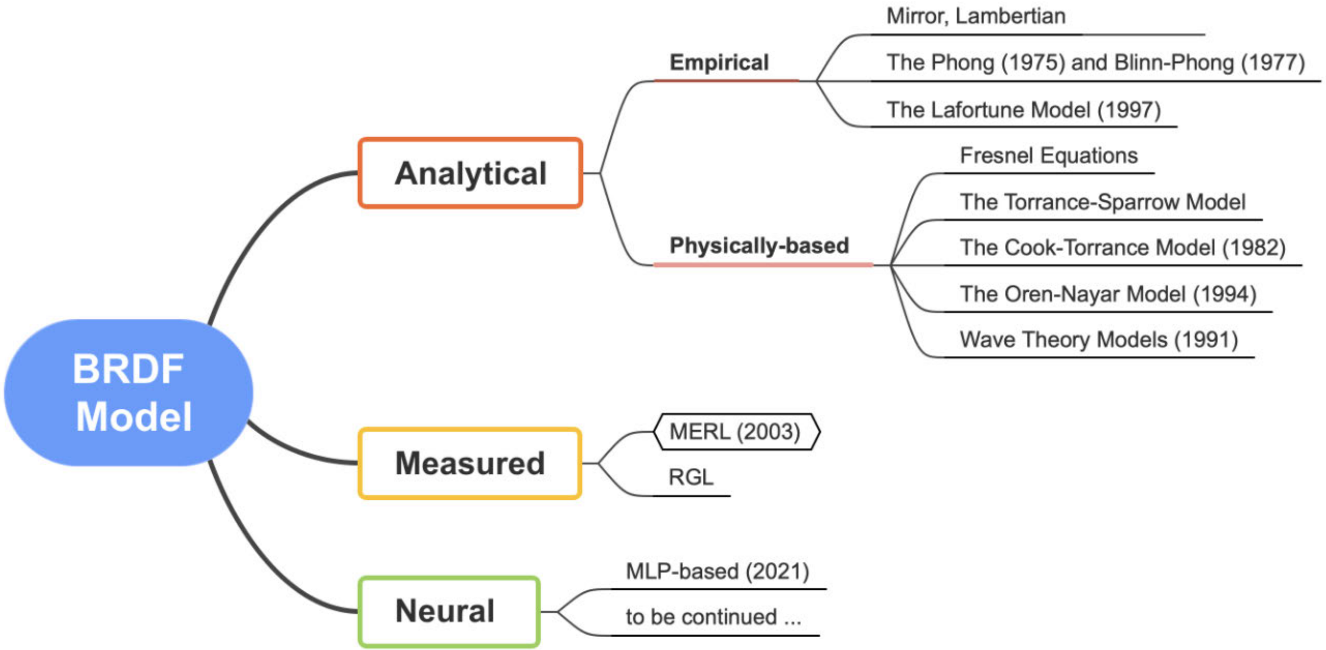

Figure A.1: An overview of BRDF representations

Datasets adopted

- MERL dataset [MPBM03], where each BRDF is stored using 90 × 90 × 180 × 3 floating point numbers
  - diverse, a total of 100, real-world captured materials.
  - data-driven property
    - such that we could apply statistical or neural network-based method on them.
- assume the materials are isotropic and spatially-identical, to reduce the complexity.
  - other advanced datasets are parts of the future work.
  - possible extensions: considering spatially-varying materials.

https://cdfg.csail.mit.edu/wojciech/brdfdatabase

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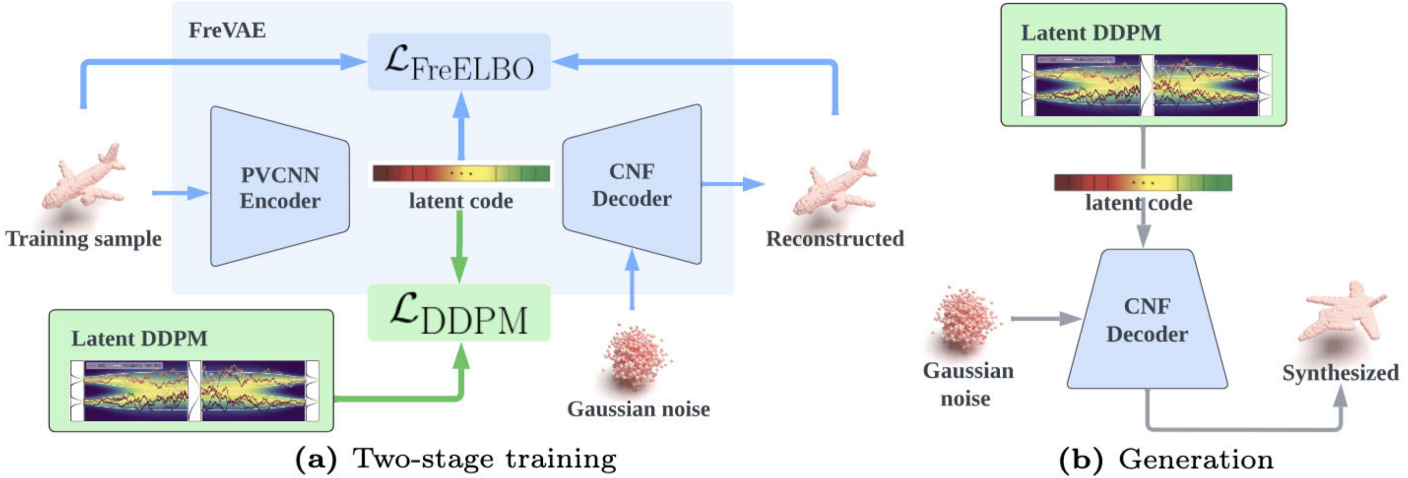
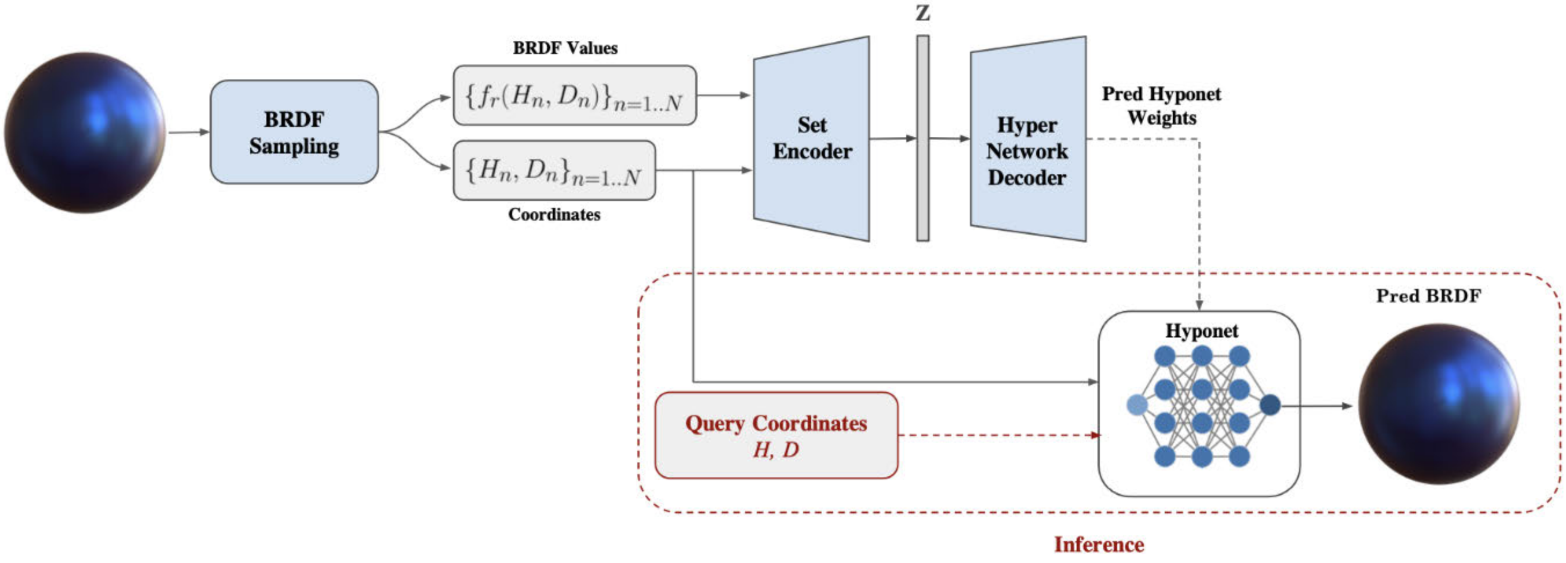


Fig. 2: FrePolad is architectured as a point cloud VAE, with an embedded latent DDPM to represent the latent distribution. (a) Two-stage training: in the first stage (blue), the VAE is optimized to maximize the FreELBO Eq. (15) with a standard Gaussian prior; in the second stage (green), while fixing the VAE, the latent DDPM is trained to model the latent distribution. (b) Generation: conditioned on a shape latent sampled from the DDPM, the CNF decoder transforms a Gaussian noise input into a synthesized shape.

https://chenliang-zhou.github.io/FrePolad/

Baseline material reconstruction method



https://faziletgokbudak.github.io/HyperBRDF/

Overview of FreNBRDF

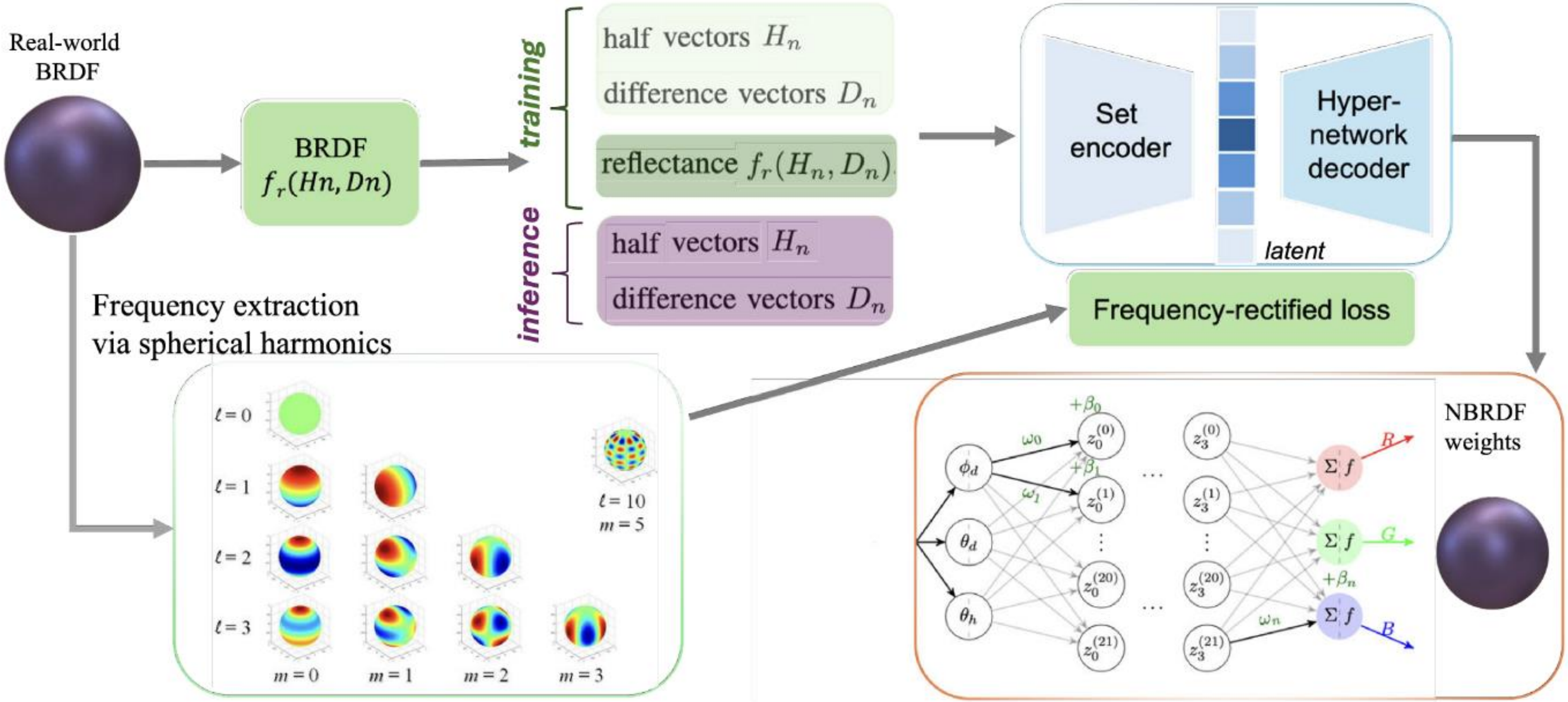


Fig. 1. Overview of FreNBRDF architecture.

Baseline vs. OUR methods

log-relative mapping

$$f_r \mapsto \ln\left(\frac{f_r + \epsilon}{f_{\text{ref}} + \epsilon}\right)$$

$$\mathcal{L}_{\text{rec}}(f_r, f_r') := \frac{1}{|P|}\sum_{i=1}^{|P|} |(f_r(H_i, D_i) - f_r'(H_i, D_i))\cos\theta_i| + \lambda_1 \sum_{i=1}^{W} w_i^2 + \lambda_2 \sum_{j=1}^{Z} z_j^2, \quad (1)$$

HyperBRDF-ECCV'24
(reconstruction loss)

Spherical harmonics

$$f_r(\theta, \varphi) = \sum_{l=0}^{\infty}\sum_{m=-l}^{l} c_{l,m} G_{l,m}(\theta, \varphi); \quad (8)$$

$$c_{l,m} = \int_0^{2\pi}\int_0^{\pi} f_r(\theta, \phi)\overline{G_{l,m}(\theta, \phi)} \sin\theta \mathrm{d}\theta \mathrm{d}\phi. \quad (9)$$

$$\mathcal{L}_{\text{fre}}(f_r, f_r') := \frac{1}{|P|}\sum_{i=1}^{|P|} \left\| c_{l,m} - c_{l,m}' \right\|^2 \quad (10)$$

Ours
(frequency-rectified loss)

https://en.wikipedia.org/wiki/Spherical_harmonics

For details, please refer to https://arxiv.org/abs/2507.00476

Frequency Rectification

$$f_r(\theta, \phi) := f_r(\theta_H, \theta_D, \phi_H = \alpha). \tag{3}$$

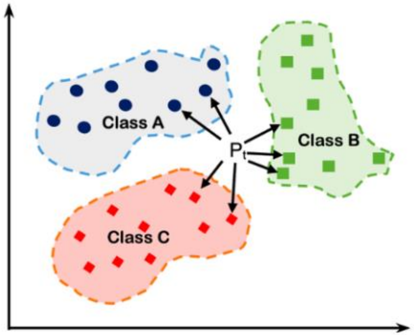
$$f_r(\theta, \phi) := \sum_{i \in P_k(\theta, \phi)} w_i f_r(\theta_i, \phi_i). \tag{4}$$

$$d_i = \sqrt{2 - 2\left[\sin\theta \sin\theta_i \cos(\phi - \phi_i) + \cos\theta\cos\theta_i\right]}. \tag{5}$$

$$w_i' := e^{-\frac{{d_i}^2}{2\sigma^2}}; \tag{6}$$

$$w_i := \frac{w_i'}{\sum_j w_j'}. \tag{7}$$

K Nearest Neighbors



Data processing and training details

- split the dataset into training, validation and testing (70%/10%/20%).
- Data Loader, Dataset module from PyTorch.
- Hyperparameter tuning grid search,
  - For example, learning rate iterates from 1e-1, 1e-3 to 1e-5. The chosen parameter, with the best performance, serves as the random search interval for finding the precise value.
- Checkpoints are used for backup and reproducibility,
  - Hyperparameter, training status are saved together with model weights. They provide the foundation for me to compare between models throughout the project and resume from history rather than training again from scratch.

Material reconstruction

Material editing

Naive baseline vs. OURS

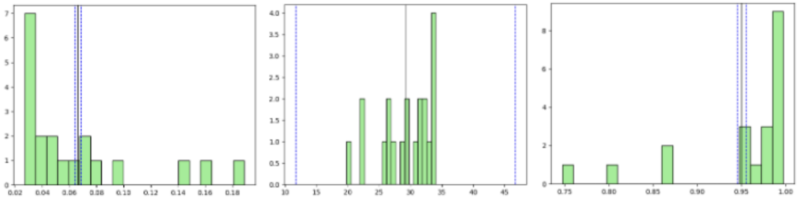
Metrics	[6]	NBRDF [4]	FreNBRDF (ours)
RMSE$\times 10^2$ ($\downarrow$)	6.89	**6.60**	6.74
PSNR ($\uparrow$)	26.3	29.2	**29.9**
SSIM$\times 10$ ($\uparrow$)	9.26	9.50	**9.88**
$\mathcal{L}_{\text{fre}} \times 10^3$ ($\downarrow$)	6.74	6.80	**0.23**

Table 1. Quantitative comparison on material reconstruction against state-of-the-art baselines. FreNBRDF achieves superior performance, showing its effectiveness.

Metrics	[6]	NBRDF [4]	FreNBRDF (ours)
RMSE$\times 10^2$ ($\downarrow$)	8.42	7.63	**6.92**
PSNR ($\uparrow$)	22.4	27.6	**30.1**
SSIM$\times 10$ ($\uparrow$)	9.13	9.42	**9.82**
$\mathcal{L}_{\text{fre}} \times 10^3$ ($\downarrow$)	6.72	6.80	**0.22**

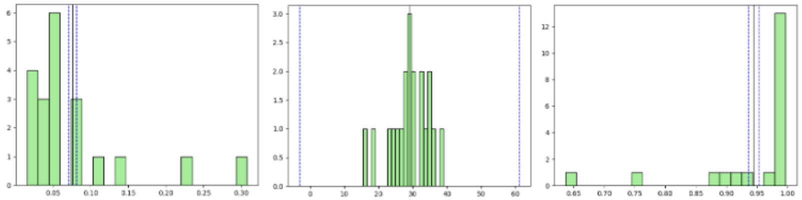
Table 2. Quantitative comparison on material editing with two state-of-the-art baselines. Materials represented by FreNBRDF exhibit significantly higher quality compared to the two baselines, indicating that FreNBRDF effectively learns the distribution of neural materials.

Naive baseline vs. OURS



(a) RMSE (b) PSNR (c) SSIM

Fig. 4. Sample-wise performance of the naive NBRDF reconstruction with mean (solid) and variance (dashed line).



(a) RMSE (b) PSNR (c) SSIM

Fig. 5. Sample-wise performance of FreNBRDF on material reconstruction, with mean (solid) and variance (dashed line).

Main takeaway

- Dataset and data processing
  - We utilize the data-driven BRDF datasets MERL and preprocess it using log-relative mapping. The dataset inputs are either in spherical or cartesian coordinate for different purposes.
- Frequency-rectified information
  - We design and implement novel ways to extract frequency information from complex high-dimensional BRDF data using spherical harmonics transformation. The extracted information serves as the input to the reconstruction task in 3D representation.
- BRDF reconstruction and editing
  - We integrate the frequency rectification information into the whole pipeline, including a brand-new loss for training.
  - A generalizable and adaptive material reconstruction and editing framework based on an autoencoder architecture, incorporating frequency rectification and achieving state-of-the-art performance.

Future work

- reconstruct isotropic BRDF by neural networks
  - other explorations worth considering, including anisotropic BRDF
  - spatially-varying BRDF and BTDF. [BSDF = BRDF + BTDF]
- physical accuracy
  - to include certain physical constraints. Hence, further dataset processing and model
  - improvements (e.g. more controls in loss functions) might be needed. With further efforts,
  - we could obtain more precise results.

Thank you for listening!

Welcome for any questions or comments!

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