Improving Angular Parameterization for Compact Neural Materials

Zilin Xu
Mohamed bin Zayed University of Artificial Intelligence
UAE

Yang Zhou
Meta Reality Labs Research
USA, Redmond

Yehonathan Litman
Meta Reality Labs Research
USA, Redmond

Ling-Qi Yan
Mohamed bin Zayed University of Artificial Intelligence
UAE

Anton Michels
Meta Reality Labs Research
USA, Redmond

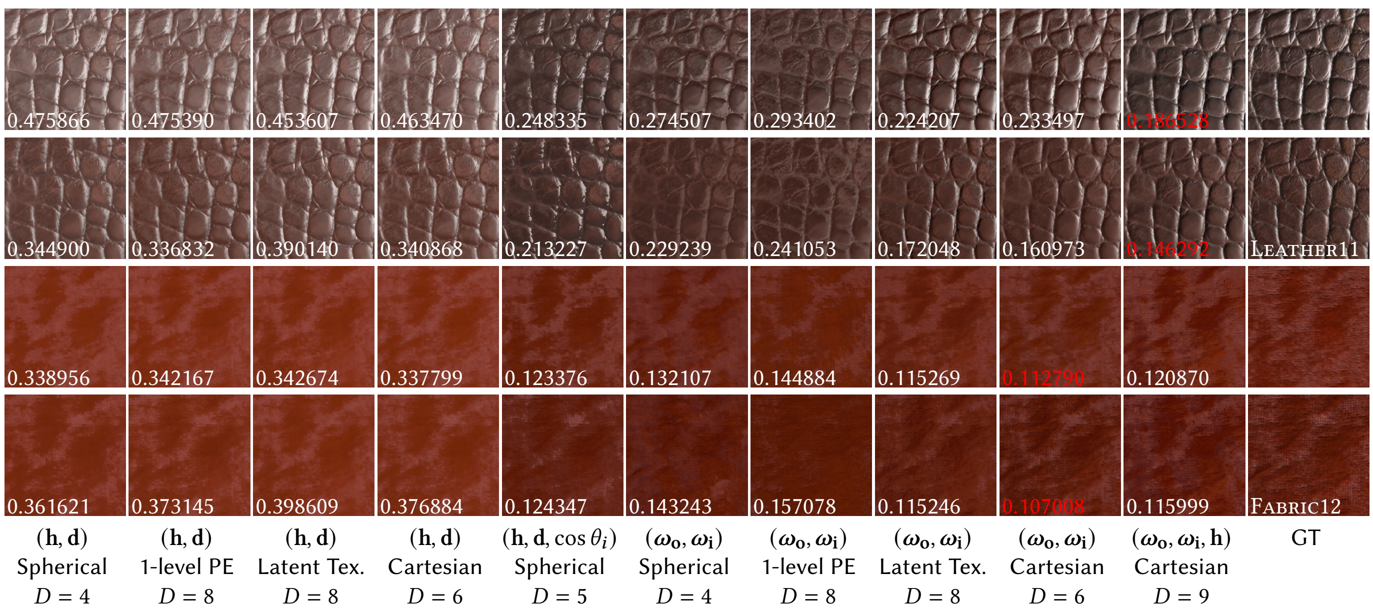

Figure 1: Each row shows the results under a different pair of input angles. We provide the image-space ꟻLIP ↓ error compared to ground truth (GT). D **is the input parameterization dimension. We linearly normalized the Spherical inputs to** $[0, 1]$**. Using** $(\omega_\mathbf{o}, \omega_\mathbf{i})$ **(optionally with** $\mathbf{h}$**) in Cartesian coordinates achieves overall better quality (lower ꟻLIP ↓).**

CCS CONCEPTS

• **Computing methodologies** → **Rendering**.

KEYWORDS

Rendering, Neural Material

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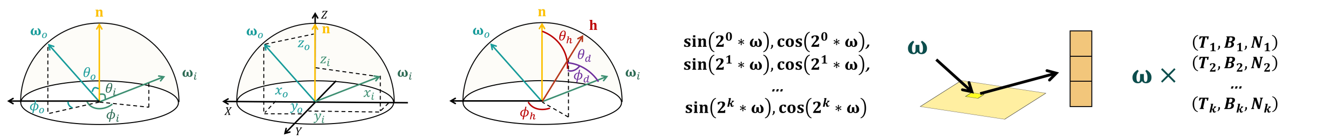
1 INTRODUCTION

Physically based rendering aims to faithfully reproduce complex appearances. Unfortunately, analytic appearance models can only achieve limited realism due to their simplified assumptions (e.g., microfacet). Recently, neural materials have emerged to learn a more accurate representation of complex appearances without explicit assumptions. Typically, a neural material is trained as multichannel neural textures with a multilayer perceptron (MLP) conditioned on angular inputs. Due to the computational cost of MLP inference which runs per-shader, the network size must be drastically reduced before deploying to real-time applications on low-power devices, such as VR headsets and phones.

We investigate the impact of different MLP input angular parameterizations on the quality of very compact neural materials.



Spherical Coordinates | Cartesian Coordinates | Rusinkiewicz Coordinates [Rusinkiewicz 1998] | Positional Encoding (PE) [Mildenhall et al. 2020] | Latent Textures [Fan et al. 2023] | Learnable Frames [Zeltner et al. 2024]

Figure 2: Common angular parameterizations for neural materials.

This design problem has been largely neglected in previous works, but we show that a suitable angular parameterization significantly improves visual quality, especially in the case of small MLP capacity.

2 OUR APPROACH

Our goal is to answer the question: Which angular parameterization is optimal for neural materials with tiny MLPs? As prefaced, such models are deployed for highly optimized low-power device rendering. Based on performance considerations, we are limited to an MLP with three 8×8 hidden layers. The output is RGB reflectance, and the input layer is $D+$ a 7-channel neural texture, where D is the dimension of the angular input ($D < 10$).

We summarize existing angular parameterizations in Fig. 2. Spherical coordinates with (θ, ϕ) and Cartesian coordinates with (x, y, z) are the two most straightforward choices. Rusinkiewicz's reparameterization [Rusinkiewicz 1998] is a popular method for neural materials [Rainer et al. 2019] that uses a half vector and a difference vector $(\mathbf{h}, \mathbf{d})$. Positional Encoding [Mildenhall et al. 2020; Xue et al. 2024] (PE) converts the input into sinusoidal functions of different frequencies. Furthermore, parameterizations can be implicitly learned and stored as latent textures [Fan et al. 2023], or indirectly obtained by learned shading frames [Zeltner et al. 2024].

Given the network size constraint, however, indirect parameterizations proved to be limited. We can only apply 1-level PE, and a 4-channel latent vector for each angle. The learnable shading frame [Zeltner et al. 2024] exceeds our budget, requiring an extra linear layer and a higher input dimension. These sophisticated methods provide no additional benefits. Instead, providing the MLP with the light falloff using $\cos(\theta_i)$ shows significant improvement. Parameterizations that include the light falloff, like using $\boldsymbol{\omega_o}, \boldsymbol{\omega_i}$ in Cartesian coordinates (where the Z-component is $\cos(\theta_i)$), consistently achieve the best quality.

3 RESULTS

We train each network with different input parameterizations from scratch on two representative measured materials from UBO2014 [Weinmann et al. 2014]: Leather11 which has complex reflection, and Fabric12 which has strong sheen.

In Fig 3, we show the average test L_1 difference over the entire dataset during training. Ours achieves the lowest error. In Fig 1, we visualize some recovered 2D slices of each parameterization. Leather11 has a complex and strong reflection; thus, the additional input $\mathbf{h}$ provides a valuable hint for learning a better reflection. However, for Fabric12, the sheen appears mostly at the grazing angles. In this case, $\mathbf{h}$ is not helpful, but rather negatively affects the quality. Nevertheless, both of the $(\boldsymbol{\omega_o}, \boldsymbol{\omega_i})$ and $(\boldsymbol{\omega_o}, \boldsymbol{\omega_i}, \mathbf{h})$ variants perform better than others.

In conclusion, we studied angular parameterizations for compact neural materials. With limited input dimensions, advanced methods fail to maintain accurate appearance, while straightforward Cartesian parameterizations achieve the best quality. Including the half vector often leads to improved handling of specular reflections.

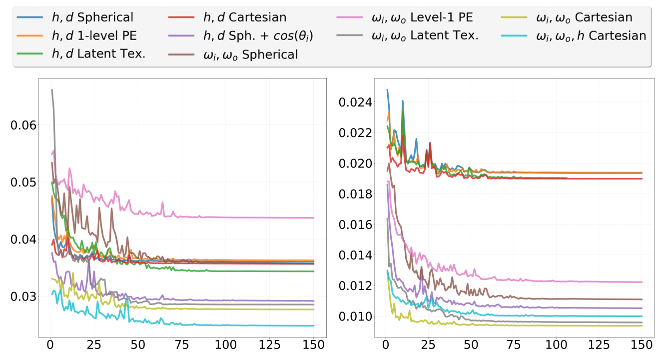


Figure 3: The L_1 test error during training. With Cartesian $\boldsymbol{\omega_o}, \boldsymbol{\omega_i}$, the overall error outperforms other parameterizations. Latent texture may have a similar loss level, but at the cost of two extra texture fetches.

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