PBR-NeRF: Inverse Rendering with Physics-Based Neural Fields

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Abstract

We tackle the ill-posed inverse rendering problem in 3D reconstruction with a Neural Radiance Field (NeRF) approach informed by Physics-Based Rendering (PBR) theory, named PBR-NeRF. Our method addresses a key limitation in most NeRF and 3D Gaussian Splatting approaches: they estimate view-dependent appearance without modeling scene materials and illumination. To address this limitation, we present an inverse rendering (IR) model capable of jointly estimating scene geometry, materials, and illumination. Our model builds upon recent NeRF-based IR approaches, but crucially introduces two novel physics-based priors that better constrain the IR estimation. Our priors are rigorously formulated as intuitive loss terms and achieve state-of-the-art material estimation without compromising novel view synthesis quality. Our method is easily adaptable to other inverse rendering and 3D reconstruction frameworks that require material estimation. We demonstrate the importance of extending current neural rendering approaches to fully model scene properties beyond geometry and view-dependent appearance. Code is publicly available at: https://github.com/s3anwu/pbrnerf.

1. Introduction

Recent advances in neural rendering and 3D reconstruction using Neural Radiance Fields (NeRF) [23] and 3D Gaussian Splatting (3DGS) [18] have driven massive research interest. However, reconstructing accurate scene properties from posed multi-view images remains a challenging, open problem due to inherent ambiguities. The material-lighting ambiguity makes the inverse rendering problem fundamentally ill-posed, with identical images being explainable by infinitely many tuples of scene materials, illumination, and geometry. Addressing this ill-posed inverse problem requires strong priors to narrow the possible solution space.

To overcome this issue, we leverage Physics-Based Rendering (PBR) theory [17, 26] from computer graphics. PBR provides a framework for generating physically accurate images given known scene materials, illumination, and geometry. By reversing this process, we derive physics-based priors to better constrain neural forward and inverse rendering and enhance estimation robustness. More specifically, while NeRF, 3DGS, and their neural field derivatives achieve state-of-the-art performance in modeling scene geometry and view-dependent appearance, they do so by treating scenes as "black boxes" that ignore the underlying physics of light transport. These methods represent light by volume-rendering millions of translucent particles, conditioning each particle's emitted radiance on its position and viewing direction. This formulation significantly improves expressiveness over traditional methods [1, 32], but it does not guarantee physically accurate results. For example, reflective surfaces may be improperly modeled, causing artifacts such as "baked-in" specular highlights, where particles emit more light in outgoing directions than physically possible. Ultimately, the performance of NeRF and 3DGS in 3D reconstruction is inherently limited by their inability to accurately and consistently model diverse light interactions.

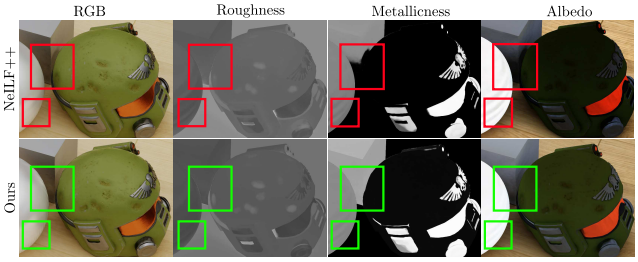

Figure 1. **Improving inverse rendering with physics-based priors.** The proposed PBR-NeRF significantly outperforms the NeILF++ [51] baseline simply by using our novel Conservation of Energy and NDF-weighted Specular Losses. Our physics-based losses correct "baked-in" specular highlights misrepresented in the diffuse lobe (highlighted areas) by (1) enforcing energy conservation and (2) accurately separating specular and diffuse reflections. The result is a more realistic, physically consistent material and lighting estimation.

In this paper, we solve the complete inverse rendering problem by jointly estimating the geometry, illumina-

tion, and materials to accurately model view-dependent appearance. We extend the NeILF/NeILF++ [44, 51] neural fields framework, combining the expressiveness of deep neural networks with the theoretical guarantees of PBR theory. Specifically, our PBR-NeRF approach improves NeILF/NeILF++'s reflection model by leveraging its underlying Disney Bidirectional Reflectance Distribution Function (BRDF) model [11]. Our method enforces energy conservation and promotes the disentanglement of the diffuse and specular lobes of the BRDF, mitigating issues such as highlights "baked in" the diffuse albedo that are commonly observed in NeRF and 3DGS reconstructions.

In particular, we achieve these goals through two novel physics-based losses applied directly to the Disney BRDF. Our first loss enforces energy conservation by penalizing physically invalid BRDFs that reflect more energy than received. Our second loss promotes the separation of specular and diffuse BRDF lobes, which is crucial for accurately modeling highly specular surfaces. Without constraints, the diffuse lobe (which defines the albedo) tends to overcompensate near symmetric reflection angles, where both lobes contribute to the aggregate BRDF. By penalizing the diffuse lobe's magnitude, weighted by the normal distribution function to target specular angles, this loss indirectly encourages the *specular lobe* to expand and fully "explain" specular highlights effectively.

We thoroughly validate PBR-NeRF on two major benchmarks for inverse rendering and novel view synthesis: the NeILF++ [51] and DTU [15] datasets. Our experiments show that PBR-NeRF sets the new state of the art for material estimation in inverse rendering, while maintaining or surpassing the competitive novel view synthesis performance of its baseline. Crucially, our model delivers faithful albedo estimates that remain consistent for a given scene across diverse illuminations, thanks to its effective diffuse-specular decomposition. This decomposition also improves metallicness and roughness estimates as an additional benefit, further highlighting the effectiveness of our approach.

2. Related Work

Neural fields for novel view synthesis have achieved impressive progress by representing 3D scenes as continuous volumetric fields [23]. This family of methods achieves photorealistic synthesis from unseen viewpoints through differentiable volume rendering, which estimates outgoing radiance by alpha-compositing color over sampled points along each camera ray. We concisely review representative works here and refer the reader to [41] for a comprehensive overview of the associated literature. Scene geometry is commonly represented using density fields [4–6, 23, 24, 28, 42, 52], 3D Gaussians [12, 18, 39], or signed distance fields (SDFs) [36, 45, 46, 49, 50] for images and other optical modalities [7, 14, 30]. While the density fields in NeRF and 3D Gaussians can model arbitrary complex scene geometries, they fundamentally lack well-defined surfaces and normals. These particle-centric representations result in ambiguous surface definitions, which hinders their applicability to PBR. In contrast, SDFs explicitly define surfaces as the zero-level set of a neural network, providing accurate surface and normal estimation. This surface-centric representation makes SDFs inherently more compatible with inverse rendering tasks which rely on PBR and require precise surface definitions.

Neural inverse rendering predates neural fields [19, 22, 31, 33, 37, 48] and learns to predict 3D geometry, materials, and illumination from 2D images. Decomposed neural fields [27, 35, 38, 47] similarly extend conventional neural fields with inverse rendering or intrinsic decomposition to estimate physical scene properties such as materials and illumination. Compared to NeRF and 3DGS, the above additional material and lighting estimation enables complex downstream tasks such as relighting [21, 29, 43], material editing, and appearance manipulation. The decomposition of reflected radiance into materials and illumination can also address issues such as "baked-in" highlights in predicted colors by properly modeling view-dependent effects. However, inverse rendering introduces significant complexity due to the material-lighting-geometry ambiguity, which is harder to lift than the geometry-radiance ambiguity of standard novel view synthesis. Many approaches simplify this task by assuming known lighting, environment map lighting [8, 9, 25, 53, 54], known geometry [44], or basic Lambertian material models. State-of-the-art inverse rendering approaches jointly model (1) direct and indirect lighting from near and far sources [40, 44, 51], and (2) spatially-varying microfacet BRDFs [34, 44, 51]. For computational efficiency, techniques such as light caching [3, 16, 20, 44, 51, 55] and incident light sampling [3, 44, 51] are crucial to avoid costly recursive light tracing.

NeILF [44] proposed joint incident light and BRDF fields, improving on environment-map-based approaches such as NeRV [34] by handling near-field lights and mixed lighting settings in addition to indirect lighting and occlusions. Building on this, NeILF++ [51] introduced inter-reflectable light fields, combining the NeILF and BRDF fields with an SDF for geometry estimation. This approach uses the SDF's volume-rendered outgoing radiance to supervise the incident radiance predicted by the NeILF. The reflection loss of [51] harnesses the SDF's strong novel view synthesis performance to steer the ill-posed inverse rendering, achieving state-of-the-art material estimation among neural inverse rendering works. While largely effective, current material estimation methods including [44, 51] lack informative material priors for disambiguating specular from diffuse properties of scene surfaces. This typically results in incorrectly attributing specular highlights to al-

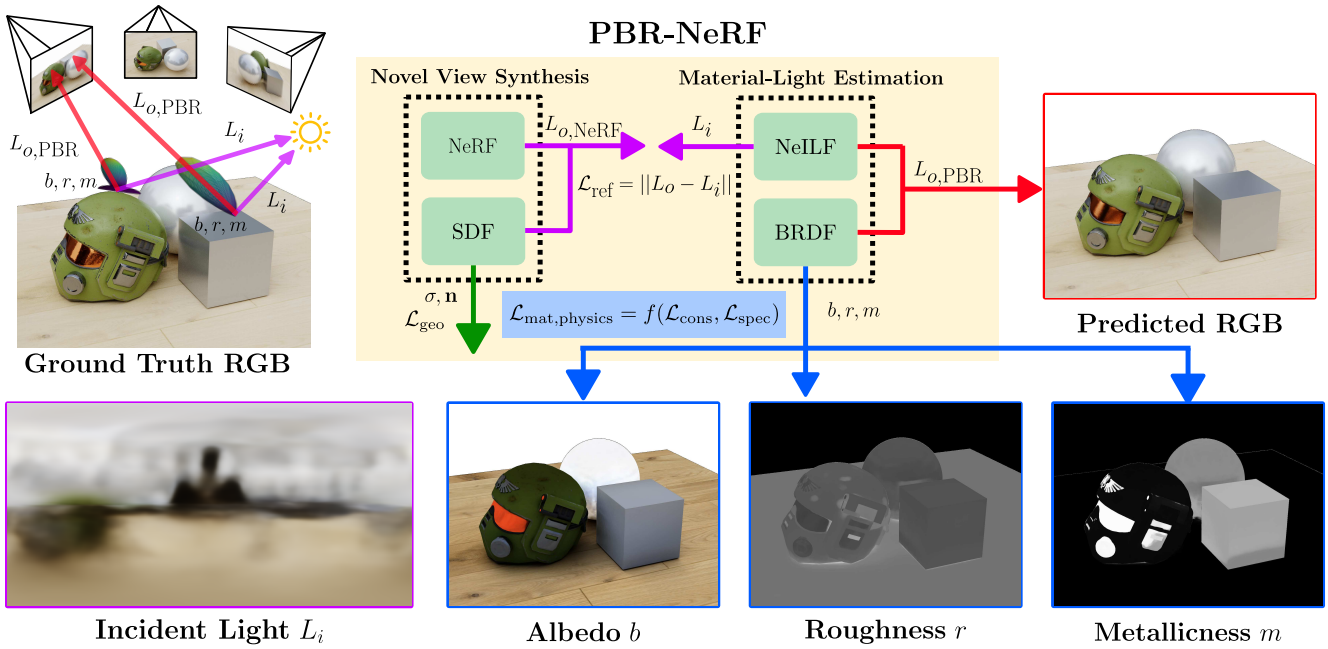

Figure 2. **Overview of our PBR-NeRF architecture for neural inverse rendering.** Our two novel physics-based material losses, i.e. $\mathcal{L}_{\text{cons}}$ for conservation of energy and $\mathcal{L}_{\text{spec}}$ for disentangling the diffuse and specular BRDF components, are derived in Sec. 3.2. The complete PBR-NeRF model comprises multiple neural fields, which are optimized in a stage-wise fashion: a standard NeRF+SDF modeling radiance and geometry, a neural incident light field (NeILF) modeling spatially-varying illumination, and a BRDF field modeling materials via the Disney BRDF [11]. Our physics-based losses provide the BRDF field with valuable inductive biases for improved material estimation, which help resolve to a large extent the inherent material-lighting ambiguity in inverse rendering and thus benefit the incident light field as well. Consequently, novel scene views synthesized with our model enjoy state-of-the-art quality.

leged changes in diffuse albedo, even though such errors do not affect view synthesis results.

Material priors for inverse rendering are crucial for constraining material estimation and reducing material-lighting ambiguities. BRDF smoothness priors [3, 16, 44, 51] can discourage abrupt spatial changes in material properties. NeILF [44] and NeILF++ [51] use a Lambertian prior to regularize the Disney BRDF's metallicness and roughness parameters. However, the Lambertian prior induces a strong assumption of perfectly rough, non-metallic materials that limits BRDF expressiveness. For instance, specular effects often appear in the predicted BRDF's diffuse lobe due to the Lambertian prior suppressing the specular lobe. We address these limitations by proposing two novel physics-based losses that enhance the physical validity and accuracy of estimated BRDFs without sacrificing expressiveness.

3. Method

We present an overview of our PBR-NeRF method with our novel Conservation of Energy and NDF-weighted Specular losses in Fig. 2.

3.1. Background

We build upon the NeILF++ [51] implicit differential renderer (IDR) as the foundation for our physics-based contributions. The IDR estimates outgoing radiance $L_o(\mathbf{x}, \boldsymbol{\omega}_o)$ by solving the Rendering Equation [17]:

$$L_o(\mathbf{x}, \boldsymbol{\omega}_o) = \int_{\Omega} f_r(\mathbf{x}, \boldsymbol{\omega}_i, \boldsymbol{\omega}_o) L_i(\mathbf{x}, \boldsymbol{\omega}_i)(\boldsymbol{\omega}_i \cdot \mathbf{n}) d\boldsymbol{\omega}_i, \quad (1)$$

where $L_o(\mathbf{x}, \boldsymbol{\omega}_o)$ is the outgoing radiance from a surface point $\mathbf{x}$ in direction $\boldsymbol{\omega}_o$, $f_r(\mathbf{x}, \boldsymbol{\omega}_i, \boldsymbol{\omega}_o)$ is the BRDF, and integration is performed over incident directions $\boldsymbol{\omega}_i$ in the positive hemisphere Ω.

To approximate the BRDF in (1), we use the simplified Disney BRDF model [11] with three spatially varying parameters: albedo (base color) $b \in [0, 1]^3$, metallicness $m \in [0, 1]$, and roughness $r \in [0, 1]$. The Disney BRDF is decomposed into a diffuse lobe $f_d(\mathbf{x})$ and a specular lobe $f_s(\mathbf{x}, \boldsymbol{\omega}_i, \boldsymbol{\omega}_o)$:

$$f_r(\mathbf{x}, \boldsymbol{\omega}_i, \boldsymbol{\omega}_o) = f_d(\mathbf{x}) + f_s(\mathbf{x}, \boldsymbol{\omega}_i, \boldsymbol{\omega}_o). \quad (2)$$

The diffuse lobe f_d models the view-independent appearance based on the albedo b and metallicness m as

$$f_d(\mathbf{x}) = \frac{1 - m(\mathbf{x})}{\pi} b(\mathbf{x}). \quad (3)$$

The specular lobe f_s models light L_o reflected in direction $\boldsymbol{\omega}_o$ due to incident radiance L_i from direction $\boldsymbol{\omega}_i$ being reflected across the halfway vector $\boldsymbol{\omega}_h = \frac{\boldsymbol{\omega}_o + \boldsymbol{\omega}_i}{||\boldsymbol{\omega}_o + \boldsymbol{\omega}_i||}$. The Disney BRDF approximates rough surface effects in the specu-

lar lobe using the microfacet BRDF model [11]. This specular lobe of the BRDF is expressed as

$$f_s(\mathbf{x}, \boldsymbol{\omega}_o, \boldsymbol{\omega}_i) = \frac{D(\boldsymbol{\omega}_h)F(\boldsymbol{\omega}_o, \boldsymbol{\omega}_h)G(\boldsymbol{\omega}_i, \boldsymbol{\omega}_o, \mathbf{n})}{4(\mathbf{n} \cdot \boldsymbol{\omega}_i)(\mathbf{n} \cdot \boldsymbol{\omega}_o)}, \quad (4)$$

where the normal distribution function (NDF) D models the distribution of microfacet orientations, the Fresnel term F models Fresnel reflections, and G models geometric occlusion. We adopt the Spherical Gaussian approximation from [44, 51, 53], in which roughness r controls the sharpness of the NDF through

$$D(\boldsymbol{\omega}_h) = \frac{1}{\pi r^4} \exp\left(\frac{2}{r^4}(\boldsymbol{\omega}_h \cdot \mathbf{n} - 1)\right). \quad (5)$$

Following NeILF++ [51], our IDR framework uses three implicit networks (cf. Fig. 2):

1. **BRDF MLP**: predicts the Disney BRDF parameters b, r, and m to compute the BRDF $f_r(\mathbf{x}, \boldsymbol{\omega}_o, \boldsymbol{\omega}_i)$.
2. **NeILF MLP**: predicts incident radiance $L_i(\mathbf{x}, \boldsymbol{\omega}_i)$.
3. **NeRF SDF**: predicts density σ (geometry) and color c, where c estimates the outgoing radiance $L_o(\mathbf{x}, \boldsymbol{\omega}_o)$.

We approximate the rendering integral in (1) according to NeILF/NeILF++ [44, 51] using a fixed set S_L of incident directions $\boldsymbol{\omega}_i$ generated by Fibonacci sampling:

$$L_o(\mathbf{x}, \boldsymbol{\omega}_o) = \frac{2\pi}{|S_L|} \sum_{\boldsymbol{\omega}_i \in S_L} f_r(\mathbf{x}, \boldsymbol{\omega}_i, \boldsymbol{\omega}_o) L_i(\mathbf{x}, \boldsymbol{\omega}_i)(\boldsymbol{\omega}_i \cdot \mathbf{n}). \quad (6)$$

To simplify notation in the following sections, we omit the arguments $\mathbf{x}$, $\boldsymbol{\omega}_i$, and $\boldsymbol{\omega}_o$ from f_r, f_d, f_s, and L_i.

3.2. Physics-Based Losses

Since inverse rendering is ill-posed, we propose two novel losses inspired by physical priors to constrain both material and lighting estimation, which are illustrated in Fig. 3.

Conservation of Energy Loss. Our first contribution addresses the non-energy-conserving behavior inherent in the Disney BRDF [11] and other microfacet models. Despite their widespread use, these models fail to conserve energy, as demonstrated in previous works [10, 13]. This limitation poses a critical challenge for inverse rendering, as it permits a material to create energy (reflect more light than received) or destroy energy (reflect too little light). Such inaccuracies skew material estimates and disrupt lighting estimation, causing the estimated illumination to overcompensate and hence appear too bright or dark. These effects cascade to downstream tasks, such as relighting and object insertion, and pose a risk for them.

To mitigate energy creation issues, we enforce the energy conservation property for the BRDF by requiring $\int_\Omega f_r(\boldsymbol{\omega}_i \cdot \mathbf{n}) d\boldsymbol{\omega}_i \leq 1$. This constraint, derived from the rendering equation (1), requires that the sum of reflected

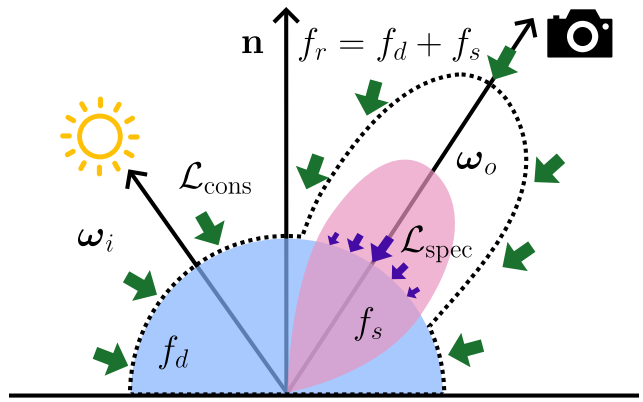

Figure 3. **Illustration of our physics-based losses**. We constrain our Disney BRDF [11] material and NeILF [44, 51] incident light estimation with two novel physics-based losses: (1) the Conservation of Energy Loss $\mathcal{L}_{\text{cons}}$ to supervise the complete BRDF $f_r = f_s + f_d$ denoted by the dotted envelope, and (2) the NDF-weighted Specular Loss $\mathcal{L}_{\text{spec}}$ to adjust the relative magnitudes of the specular f_s (red) and diffuse f_d (blue) BRDF lobes.

radiance weights $f_r(\boldsymbol{\omega}_i \cdot \mathbf{n})$ across all incident directions in the hemisphere Ω must not exceed unity. By enforcing this intrinsic physical property, independent of incident lighting, we ensure physically correct materials.

We reformulate this constraint in our discretized setting as the Conservation of Energy Loss:

$$\mathcal{L}_{\text{cons}} = \max\left\{\left(\frac{2\pi}{|S_L|} \sum_{\boldsymbol{\omega}_i \in S_L} f_r(\boldsymbol{\omega}_i \cdot \mathbf{n})\right) - 1, 0\right\}. \quad (7)$$

This ReLU-style formulation prevents overestimation of reflected light, allowing reflected irradiance to vary but without exceeding the incident irradiance. We only penalize the model when the sum of weights $f_r(\boldsymbol{\omega}_i \cdot \mathbf{n})$ exceeds 1, but any value below can freely vary. As seen in Fig. 3, the Conservation of Energy Loss affects both specular and diffuse lobes, ensuring that the overall BRDF f_r conserves energy.

NDF-weighted Specular Loss. Our second physics-based loss targets the imbalance between the diffuse and specular lobes frequently observed in inverse rendering methods, such as NeILF++ [51], which often assume Lambertian reflection. Real-world materials, however, often violate idealized Lambertian behavior, resulting in "baked-in" specular highlights where the predicted diffuse lobe f_d overcompensates for insufficient specular reflection. For these "baked-in" specular highlights, the aggregate BRDF value f_r may be accurate for specular directions, but the imbalance between f_d and f_s causes incorrect diffuse behavior at non-specular angles, degrading material estimation quality.

To correct this imbalance, we propose the NDF-weighted Specular Loss to penalize excessive diffuse reflection in

specular regions and we define our loss as

$$\mathcal{L}_{\text{spec}} = \frac{1}{|S_L|} \sum_{\boldsymbol{\omega}_i \in S_L} \text{softmax}\left(\frac{\text{detach}\left(D\left(\frac{\boldsymbol{\omega}_o + \boldsymbol{\omega}_i}{||\boldsymbol{\omega}_o + \boldsymbol{\omega}_i||} \right) \right)}{T_{\text{spec}}} \right) f_d, \tag{8}$$

where D is the NDF evaluated using the halfway vector $\frac{\boldsymbol{\omega}_o+\boldsymbol{\omega}_i}{||\boldsymbol{\omega}_o+\boldsymbol{\omega}_i||} = \boldsymbol{\omega}_h$. By using a softmax-weighted NDF with temperature T_{spec}, we selectively penalize diffuse reflections in regions where specular effects dominate. We detach the NDF term from the computation graph to prevent gradient flow through $D(\boldsymbol{\omega}_h)$ during backpropagation, ensuring that only diffuse contributions to $\mathcal{L}_{\text{spec}}$ result in weight updates.

Our NDF-weighted Specular Loss complements the standard RGB rendering loss by pushing the specular lobe f_s to compensate for the penalized diffuse lobe f_d, creating a stronger separation between diffuse and specular reflections. A proper weighting of the opposing RGB rendering loss and other regularization terms ensures that the diffuse lobe is not arbitrarily suppressed by our specular loss. As with $\mathcal{L}_{\text{cons}}$, the specular loss also benefits lighting estimation. An oversized diffuse lobe can lead to underestimated light intensities, and excessive diffuse reflection can also force the estimated incident light to incorrectly reproduce complex, view-dependent specular effects. Together, our two losses $\mathcal{L}_{\text{cons}}$ and $\mathcal{L}_{\text{spec}}$ significantly improve the accuracy of material and lighting estimation, resulting in more realistic scene reconstructions, as we detail in Sec. 4.

3.3. Joint Optimization

Following NeILF++ [51], we optimize the scene reconstruction in three phases. We briefly summarize the three phases here (full details are provided in the supplement):

1. **Geometry**: only train NeRF SDF to initialize estimated geometry using a geometry-based loss $\mathcal{L}_{\text{geo}}$.
2. **Material**: train NeILF and BRDF MLPs while freezing the NeRF SDF to initialize estimated illumination and materials with a material-based loss $\mathcal{L}_{\text{mat}}$.
3. **Joint Optimization**: train all fields (NeRF SDF, NeILF, BRDF) with all losses $\mathcal{L} = \mathcal{L}_{\text{geo}} + \mathcal{L}_{\text{mat}}$.

Each phase uses different losses that encode specific priors or constraints relevant to that phase. The full material-based loss including our complete physics-based loss $\mathcal{L}_{\text{mat,physics}}$ is

$$\mathcal{L}_{\text{mat}} = \lambda_{\text{pbr}}\mathcal{L}_{\text{pbr}} + \lambda_{\text{ref}}\mathcal{L}_{\text{ref}} + \lambda_{\text{smth}}\mathcal{L}_{\text{smth}} + \mathcal{L}_{\text{mat,physics}}, \tag{9}$$

where $\mathcal{L}_{\text{mat,physics}} = \lambda_{\text{cons}}\mathcal{L}_{\text{cons}} + \lambda_{\text{spec}}\mathcal{L}_{\text{spec}}$ includes our Conservation of Energy Loss and our NDF-weighted Specular Loss, $\mathcal{L}_{\text{pbr}}$ is a standard RGB rendering loss supervising the estimated outgoing radiance from (6), $\mathcal{L}_{\text{ref}}$ is the NeILF++ reflection loss [51], $\mathcal{L}_{\text{smth}}$ is the NeILF/NeILF++ BRDF smoothness loss [44, 51], and $\lambda_{\text{pbr}}, \lambda_{\text{ref}}, \lambda_{\text{smth}}, \lambda_{\text{cons}}, \lambda_{\text{spec}}$ are positive weights.

4. Experiments

4.1. Experimental Setup

Implementation Details. We implement PBR-NeRF on top of NeILF++ [51] using PyTorch [2] and keep all hyperparameters from NeILF++ the same, except for $|S_L| = 256$ and a training batch size of 8192 rays. The geometry, material, and joint phases last 5K, 1K, and 30K iterations, respectively. We train with a learning rate of 0.002, which is fixed for the geometry and material phase, but decreases by a factor of 5 every 10K iterations during the joint phase. Training runs on a single NVIDIA A6000, with runtimes ranging from 3 to 7.5 hours. Using grid search, we identify two sets of weights for our physics-based losses: $\lambda_{\text{cons}} = 0.01$ and $\lambda_{\text{spec}} = 0.5$ for the NeILF++ dataset, and $\lambda_{\text{cons}} = 0.01$ and $\lambda_{\text{spec}} = 0.01$ for DTU. We weigh λ_{spec} lower than the RGB loss, $\lambda_{\text{pbr}} = 1$, so that $\mathcal{L}_{\text{spec}}$ has a small yet meaningful weighting. More hyperparameter details are provided in the supplement.

Datasets. We evaluate our method on the NeILF++ [51] and DTU [15] datasets. We use the NeILF++ synthetic dataset to evaluate our material-illumination estimation, assuming known geometry. This dataset provides ground-truth geometry, RGB, albedo, metallicness, and roughness for a scene rendered under 6 static illumination patterns, including three environment maps (Env) and three mixed-lighting scenarios with additional point and area light sources (Mix). Each pattern includes 96 RGB HDR 1600×1200 images, split into 87 training and 9 validation images. Ground-truth geometry and poses are used in training, while ground-truth color, albedo, metallicness, and roughness are only used for evaluation. DTU captures 15 real-world objects in a controlled lab setting. Each scene includes 49 RGB LDR 1600×1200 images, split into 44 training and 5 validation images. We evaluate the predicted geometry by computing the Chamfer Distance with the provided reference point cloud generated by structured light scanners. We only qualitatively evaluate material estimation on DTU because it uses LDR images and does not provide ground-truth materials. We do not evaluate lighting because the DTU dataset is unsuitable for evaluating predicted lighting without HDR images and ground-truth environment maps. Furthermore, the predicting lighting is not meaningful because lighting cannot be reliably estimated from the LDR DTU images due to clipping and unknown tone mapping.

4.2. Comparison with The State of The Art

Quantitative Results. Table 1 shows that PBR-NeRF achieves state-of-the-art material estimation on the NeILF++ dataset, outperforming previous methods by 1–3 PSNR on average across albedo, metallicness, and roughness. We outperform all baselines in roughness and metal-

Table 1. **Comparison against state-of-the-art methods on the NeILF++ dataset [51].** Material estimation and novel view synthesis are compared across different scenes (City, Studio, and Castel) and types of illumination (Env: global environment map, Mix: mixed lighting with environment map, point, and area light sources) using PSNR and SSIM. †: our reproduced results. N/A: no official reported results.

Predicted Quantity	Method	Env-City		Env-Studio		Env-Castel		Mix-City		Mix-Studio		Mix-Castel		Mean	
		PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
RGB	PhySG [53]	24.82	N/A	25.65	N/A	27.24	N/A	24.38	N/A	24.04	N/A	25.81	N/A	25.32	N/A
	SG-ENV [53]	31.01	N/A	29.46	N/A	32.34	N/A	27.20	N/A	25.88	N/A	27.70	N/A	28.93	N/A
	NeILF [44] †	**33.23**	92.29	**31.12**	**83.55**	**36.21**	**94.13**	30.00	86.95	27.56	74.20	30.91	89.83	**31.50**	86.83
	NeILF++ [51]†	31.53	91.51	29.77	80.15	33.87	93.26	29.64	88.83	27.50	74.70	30.74	91.07	30.51	86.59
	PBR-NeRF (ours)	32.60	**92.33**	30.96	80.77	34.88	93.66	**30.03**	**89.17**	**27.84**	**75.01**	**31.34**	**91.39**	31.27	**87.05**
Roughness	PhySG [53]	6.62	N/A	11.29	N/A	6.22	N/A	6.27	N/A	6.83	N/A	6.14	N/A	7.23	N/A
	SG-ENV [53]	9.61	N/A	17.64	N/A	9.74	N/A	8.77	N/A	12.58	N/A	9.14	N/A	11.25	N/A
	NeILF [44]†	16.71	86.77	17.72	86.48	18.05	89.56	15.11	81.42	14.54	78.53	15.04	81.28	16.19	84.01
	NeILF++ [51]†	21.22	91.27	22.01	91.89	19.91	90.63	**22.19**	91.57	**23.43**	92.37	**22.20**	91.61	21.83	91.56
	PBR-NeRF (ours)	**22.19**	**92.32**	**23.45**	**92.74**	**22.23**	**92.07**	22.15	**92.04**	22.63	**92.57**	22.18	**92.10**	**22.47**	**92.31**
Metallicness	PhySG [53]	8.72	N/A	7.97	N/A	8.35	N/A	8.67	N/A	8.95	N/A	8.76	N/A	8.57	N/A
	SG-ENV [53]	17.01	N/A	16.40	N/A	16.39	N/A	15.44	N/A	14.25	N/A	14.49	N/A	15.66	N/A
	NeILF [44]†	19.48	64.43	18.75	92.56	18.21	**92.58**	21.03	65.53	**19.45**	**89.85**	19.60	76.44	19.42	80.23
	NeILF++ [51]†	19.49	**86.50**	18.17	**92.99**	17.41	91.92	20.80	**80.48**	19.18	68.74	17.98	**80.14**	18.84	**83.46**
	PBR-NeRF (ours)	**21.73**	72.66	**22.26**	73.26	**20.88**	88.65	**22.45**	68.40	19.24	63.25	**23.15**	78.28	**21.62**	74.08
Albedo	PhySG [53]	15.01	N/A	16.96	N/A	16.13	N/A	14.16	N/A	12.43	N/A	14.29	N/A	14.83	N/A
	SG-ENV [53]	**22.38**	N/A	**20.74**	N/A	**22.21**	N/A	16.92	N/A	13.16	N/A	16.69	N/A	18.68	N/A
	NeILF [44]†	17.73	90.32	21.11	**90.21**	18.24	90.18	17.01	77.14	18.52	**81.01**	16.32	78.33	18.15	84.53
	NeILF++ [51]†	18.21	82.62	19.50	79.21	17.73	82.48	16.37	70.13	14.48	64.61	17.43	76.20	17.29	75.87
	PBR-NeRF (ours)	19.59	**90.60**	20.24	88.33	19.88	**91.45**	**20.18**	**85.53**	**19.44**	77.86	**21.14**	**87.13**	**20.08**	**86.82**

Table 2. **Comparison for novel view synthesis against state-of-the-art methods on DTU [15].** Performance is compared across different scenes using the RGB PSNR and Chamfer Distance metrics. †: our reproduced results. ‡: mean result over 3 runs. *: only 1 of either RGB PSNR or Chamfer Distance results is publicly available.

	Method \ DTU scan	24	37	40	55	63	65	69	83	97	105	106	110	114	118	122	Mean$\pm\sigma$
RGB PSNR	NeRFactor [54]*	23.24	21.91	23.33	26.86	22.70	24.71	**27.59**	22.56	20.45	25.08	26.30	25.14	21.35	26.44	26.53	24.28
	PhySG [53]*	17.38	15.11	20.65	18.71	18.89	18.47	18.08	21.98	17.31	20.67	18.75	17.55	21.20	18.78	23.16	19.11
	NeILF++ [51]†‡	25.85	21.93	25.42	27.99	29.76	27.45	26.54	28.37	23.73	28.28	31.56	30.45	26.86	31.32	32.19	27.85$\pm$1.04
	PBR-NeRF (ours)‡	**26.11**	**24.49**	**27.56**	**28.30**	**30.13**	**27.57**	27.07	**29.89**	**24.76**	**28.71**	**31.83**	**30.68**	**27.24**	**31.64**	**33.48**	**28.63** $\pm$ 0.29
Chamfer Distance [mm]	VolSDF [46]*	0.810	1.140	0.490	1.250	0.700	0.720	1.290	1.180	**1.260**	**0.700**	0.660	1.080	0.420	0.610	0.550	0.857
	NeuS [36]*	0.930	**1.000**	**0.430**	1.100	**0.650**	**0.570**	1.480	**1.090**	1.370	0.830	**0.520**	1.200	**0.350**	**0.490**	0.540	0.837
	NeILF++ [51]†‡	**0.748**	3.028	1.285	**0.448**	1.627	0.640	1.287	1.649	2.697	1.008	0.604	0.745	0.397	0.513	0.824	1.167$\pm$0.68
	PBR-NeRF (ours)‡	0.816	1.343	0.486	0.511	1.665	0.688	**0.647**	1.174	1.416	1.038	0.590	**0.676**	0.398	0.502	**0.468**	**0.828**$\pm$0.09

licness PSNR in most scenes across all illuminations. For albedo, we observe substantial gains in PSNR and SSIM over all competitors both on overall average and in Mix lighting scenarios, which are generally more complex due to their combined lighting setups. Our closest competitor for albedo estimation is SG-Env, which combines the PhySG [53] Spherical Gaussian (SG) lighting representation with a spatially-varying microfacet BRDF. SG-Env estimates albedo better on the Env scenes since its explicit SG lighting models environment lighting better than PBR-NeRF's under-constrained implicit lighting MLP. However, PBR-NeRF performs over 3 albedo PSNR better than SG-Env on the more challenging Mix scenes, as SGs cannot model spatially varying illumination such as mixed light sources, indirect lighting, and occlusions. While SG-Env struggles with mixed, SV lighting, PBR-NeRF estimates albedo equally well *across* environment and mixed lighting. Despite performing slightly worse than NeILF [44] and NeILF++ [51] in metallicness SSIM, we outperform all competitors in all other material estimation metrics.

Among inverse rendering methods, PBR-NeRF achieves state-of-the-art results in novel view synthesis and geometry estimation on DTU, as shown in Table 2. We report the average results and standard deviation over three training runs both for our approach and NeILF++ [51], mitigating the impact of training variability. Our method achieves an improvement of 0.78 in mean PSNR and 0.339 mm in Chamfer Distance over NeILF++ with lower variance, showing that our proposed losses positively impact geometry estimation too. Additionally, PBR-NeRF ranks first in 14 scenes for RGB PNSR, with PSNR gains ranging from 0.12 to 2.56 over NeILF++, demonstrating consistent improvements over our closest baseline, and it substantially outperforms all other methods.

Qualitative Results. We further validate our material estimation performance qualitatively against NeILF++ on the NeILF++ dataset in Fig. 4 (see supplement for additional qualitative results). Over all three challenging Mix lighting conditions, our physics-based losses improve both lighting and material estimation. Our estimated lighting exhibits lower entropy with more concentrated sources and fewer artifacts, especially in the upper halves of environment maps. We also eliminate fringes and patches generated on the sphere and cube by NeILF++ due to "baked-in" specular highlights and achieve effective separation of diffuse and specular BRDF components via our NDF-weighted Spec-

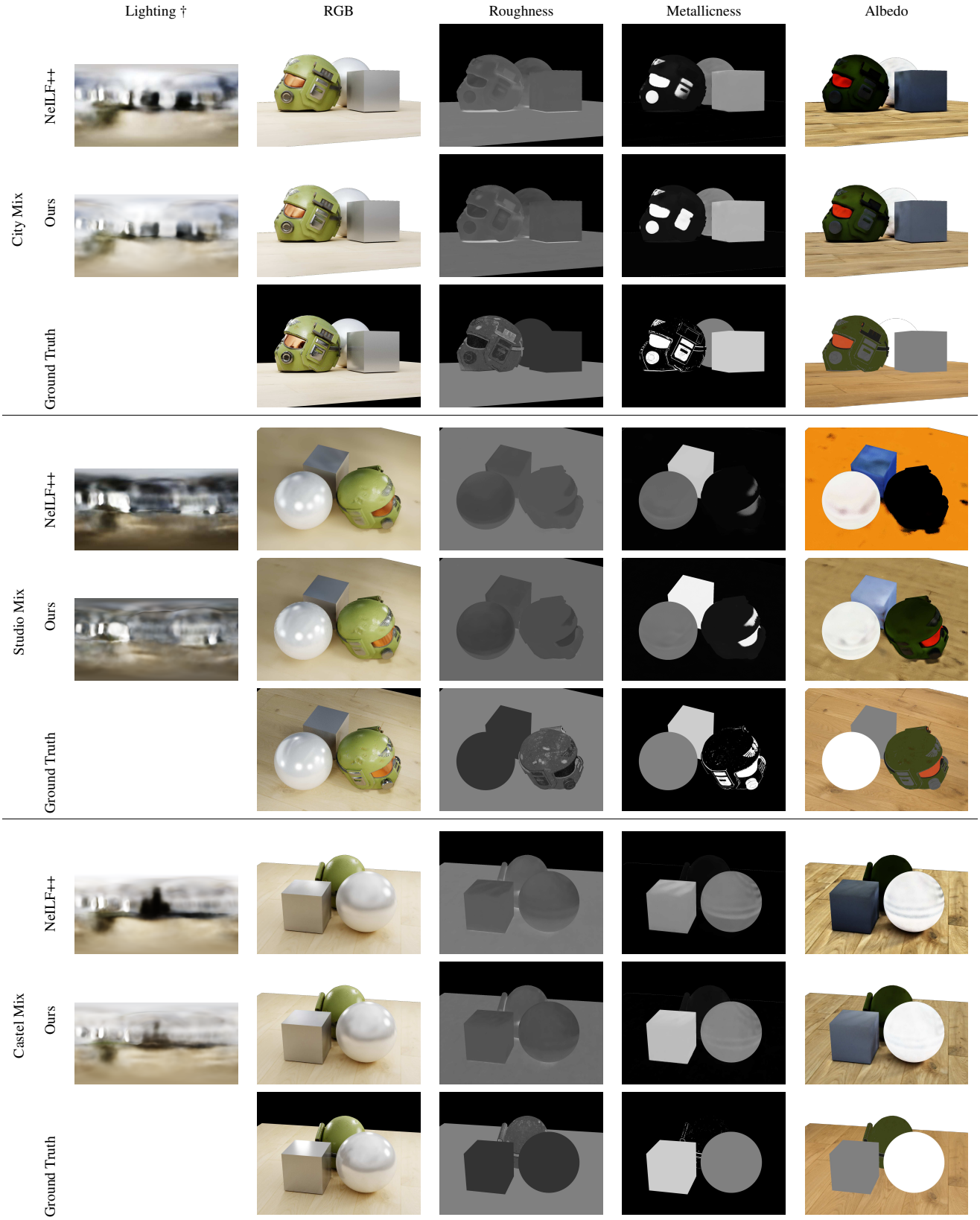

Figure 4. **Qualitative comparisons on the NeILF++ dataset [51].** †: no ground-truth environment maps are provided with the dataset.

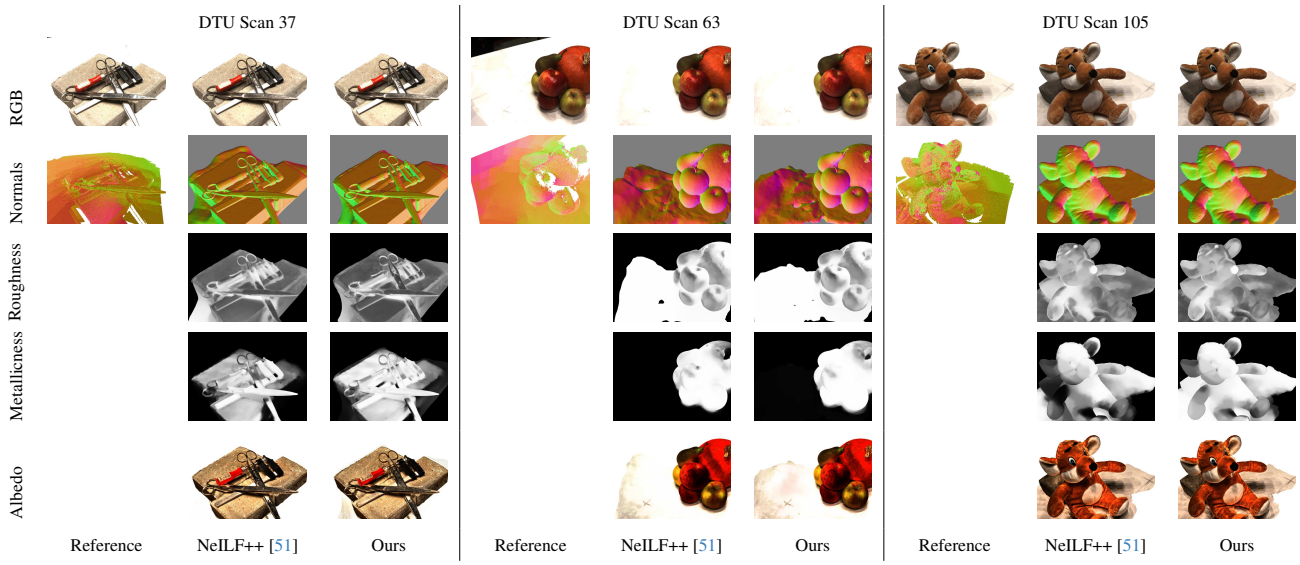

Figure 5. **Qualitative comparisons on DTU [15].** Best viewed on a screen at full zoom.

ular Loss. Most importantly, we consistently outperform NeILF++ on albedo estimation, which is a critical challenge in inverse rendering. In particular, our albedo estimation in Studio Mix properly recovers the helmet and visor whereas NeILF++ fails to recover any helmet details and incorrectly predicts a black albedo. In general, our predicted albedo is—correctly—less bright than for NeILF++, with the floor, cube, and sphere all free from incorrect specular highlights and artifacts.

We compare our DTU material and geometry estimation in Fig. 5. On scan 37, we improve metallicness and roughness, accurately predicting the scissor and clamp as metal, unlike NeILF++, which creates artifacts near the scissor handle in its predicted normals, metallicness, and roughness. On scan 63, we successfully recover fine details like the green apple stem, which NeILF++ misses in its predicted normals and materials. On scan 105, we correctly reproduce the brick's top surface, whereas NeILF++ has RGB, normals, and albedo artifacts. Our roughness and metallicness on the orange toy fur are also more consistent than NeILF++ for the homogeneous furry material.

4.3. Ablation Study

We perform an ablation study of the proposed physically-based losses in Tab. 3 to individually evaluate each loss's contribution. A qualitative analysis is provided in the supplement. The baseline (ID 1) is NeILF++ [51] without the Lambertian loss. Adding only the Conservation of Energy Loss $\mathcal{L}_{\text{cons}}$ (ID 2) improves material estimation, with albedo PSNR increasing by 2.34 and roughness PSNR by 0.28, respectively. Adding only the specular loss $\mathcal{L}_{\text{spec}}$ (ID 3) also improves material estimation over ID 1, with albedo PSNR increasing by 2.35, roughness PSNR by 0.25, and metallicness PSNR by 0.26, respectively. In our final method (ID 4), adding both $\mathcal{L}_{\text{cons}}$ and $\mathcal{L}_{\text{spec}}$ achieves the highest albedo, roughness, and metallicness PSNR. Specifically, albedo PSNR and SSIM increase by an additional 0.93 PSNR and 1.84% over ID 3, respectively. Although metallicness SSIM is lower for ID 2–4 compared to ID 1, metallicness PSNR is improved. Overall, our complete method (ID 4) with both physics-based losses improves roughness by 0.35 PSNR, metallicness by 0.27 PSNR, and albedo by 3.28 PSNR over the baseline (ID 1), while maintaining on-par performance in RGB.

Table 3. **Ablation of our physics-based losses.** Performance of ablated versions of PBR-NeRF and of its full version is compared on the mean PSNR and SSIM of *all* 6 scenes of the NeILF++ dataset [51] for Disney BRDF parameters and novel views.

ID	$\mathcal{L}_{\text{cons}}$	$\mathcal{L}_{\text{spec}}$	RGB		Roughness		Metallicness		Albedo	
			PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
1	✗	✗	31.26	87.05	22.12	92.20	21.35	74.98	16.80	74.04
2	✓	✗	31.29	87.09	22.40	92.31	21.30	72.42	19.14	84.30
3	✗	✓	31.27	87.05	22.37	92.32	21.61	73.58	19.15	84.98
4	✓	✓	31.27	87.05	22.47	92.31	21.62	74.08	20.08	86.82

5. Conclusion

We present PBR-NeRF, a novel inverse rendering method leveraging neural fields optimized with PBR-inspired losses. These losses provide physically valid inductive biases, enabling our neural fields to better disambiguate materials from lighting—addressing a major challenge in inverse rendering. Thorough experiments across various benchmarks demonstrate the effectiveness of PBR-NeRF not only in material estimation and inverse rendering, but also in novel view synthesis. In particular, we qualitatively show a compelling disentanglement of the diffuse and specular components in our estimated BRDFs. We believe that our physics-based approach will inspire further work on PBR-driven, decomposed neural fields.

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