3D Scene Creation and Rendering via Rough Meshes: A Lighting Transfer Avenue

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Abstract—This paper studies how to flexibly integrate reconstructed 3D models into practical 3D modeling pipelines such as 3D scene creation and rendering. Due to the technical difficulty, one can only obtain rough 3D models (R3DMs) for most real objects using existing 3D reconstruction techniques. As a result, physically-based rendering (PBR) would render low-quality images or videos for scenes that are constructed by R3DMs. One promising solution would be representing real-world objects as Neural Fields such as NeRFs, which are able to generate photo-realistic renderings of an object under desired viewpoints. However, a drawback is that the synthesized views through Neural Fields Rendering (NFR) cannot reflect the simulated lighting details on R3DMs in PBR pipelines, especially when object interactions in the 3D scene creation cause local shadows. To solve this dilemma, we propose a lighting transfer network (LighTNet) to bridge NFR and PBR, such that they can benefit from each other. LighTNet reasons about a simplified image composition model, remedies the uneven surface issue caused by R3DMs, and is empowered by several perceptual-motivated constraints and a new Lab angle loss which enhances the contrast between lighting strength and colors. Comparisons demonstrate that LighTNet is superior in synthesizing impressive lighting, and is promising in pushing NFR further in practical 3D modeling workflows.

Index Terms—3D scene creation, scene synthesis, lighting transfer, neural rendering, physically-based rendering.

I. INTRODUCTION

The computer vision and graphics communities have put tremendous efforts into studying objects’ representation methods for 3D modeling over the past years. In practical 3D modeling pipelines such as 3D scene designing, augmented reality (AR), and robotics, objects are usually represented as 3D CAD meshes combined with their materials and texture atlases (denoted as 3DMs). However, even the state-of-the-art (SOTA) 3D reconstruction methods do not have very accurate mesh reconstructions [1], [2], [3], [4], [5]. As a consequence, physical-based rendering (PBR) can only render low-quality content from these rough 3D models (R3DMs).

In this paper, we study how to flexibly integrate reconstructed 3D models into practical 3D modeling pipelines such as 3D scene creation and rendering. More specifically, we consider a practical setting in which one can utilize R3DMs (or R3DMs together with 3DMs) to create any scenes and assign arbitrary lighting to each created scene. Our goal is to render high-quality content from these possible scenes without training (or fitting) the newly created scenes. A possible solution is to represent real-world objects as Neural Fields such as NeRF [6] in addition to R3DMs. Specifically, in the design process, the primary role of a 3D model lies in interaction (with the environment and with light). If we can obtain information about these interactions (such as the effects of various lights on objects) through physical rendering, and then combine this with NeRF to acquire high-precision appearance information, we can use neural networks to simulate the process of rendering element composition. This enables us to mitigate the impact of rough 3D models and obtain high-precision scene renderings. As shown in Fig. 1, given both the explicit representations (R3DMs) and implicit representations (NeRFs) of several real-world objects, artists can create unlimited 3D scenes in graphics software, then freely render high-quality images and videos by simply compositing PBR images and NFR images.

In further, artists may perform free lighting simulation to their created 3D scenes (e.g., setting several strong light sources) to capture realistic renderings. The remained question is that the above rendering routing cannot reflect the simulated lighting details on R3DMs in PBR pipelines, especially when object interactions in the 3D scene creation cause local shadows. Some works on neural light fields [7], [8], [9], [10], [11], [12] learn to simulate arbitrary lighting to an object or a scene. Still, they cannot model the complex local shadows without fitting a static scene under many possible lighting conditions. Thus, these light field methods would require training on each newly created scene under different lighting conditions, which is impractical for real-world applications.

To solve the dilemma, we propose a Lighting Transfer Network (LighTNet) to bridge NFR and PBR, such that they can benefit from each other. LighTNet takes “Shading” rendered from a PBR system and a synthesized image by NFR techniques (e.g., NeRF) as input and outputs photo-realistic renderings with rich lighting details. Taking inspiration from the image composition process in V-Ray [13], we prudently reformulate it to remedy the non-smooth “Shading” surfaces caused by R3DMs as well as better preserve lighting details. Furthermore, we propose perceptual-motivated constraints to optimize LighTNet...
Fig. 1. Lighting transfer avenue. Left (Problem): Given some reconstructed rough 3D models (R3DMs) and designed 3D CAD models (3DMs), artists can use them to create any 3D scenes and freely perform arbitrary lighting simulation for each created scene. A physically-based rendering (PBR) system can only render low-quality images or videos for these scenes. Our goal is to render high-quality content from these possible scenes without training (or fitting) the newly created 3D scenes.

Right (Solution): As an example, if we have pre-obtained a neural fields representation (e.g., NeRF [6]) for each real object, we can synthesize object instances for R3DMs in impressive quality through neural fields rendering (NFR). Unluckily, NFR instances cannot reflect the simulated lighting details (e.g., local shadows) on R3DMs. We propose a lighting transfer network (LighTNet) to bridge NFR and PBR, such that they can benefit from each other. In practice, LighTNet is trained once in a dataset and can be used for all the newly created 3D scenes with both seen and unseen R3DMs and arbitrary lighting (See “Generalizing to Real-Lighting” in Fig. 11).

In summary, our main contributions are as follows:

- We present a lighting transfer avenue that allows artists to create arbitrary 3D scenes, flexibly simulate lighting, and freely render photo-realistic images and videos via R3DMs and 3DMs in any graphic software.
- With the pathway, we develop a lighting transfer network (LighTNet) leveraging a prudently reformulated image composition formulation. This network effectively bridges the lighting gap between PBR and NFR, showing promise in addressing the non-smooth “Shading” surfaces resulting from R3DMs.
- We introduce a Lab Angle loss to enhance the contrast between lighting strength and colors which can further improve the rendering quality.

II. RELATED WORK

A. 3D Object Reconstruction

Typical SFM and MVS approaches [14], [15], [16] can reconstruct 3D meshes of objects that are with rich textures in reasonable quality. Leveraging large database, researchers exploit deep neural networks to reconstruct point clouds [17], [18], [19], [20], voxel grids [21], [22], [23], [24], [25], and meshes [26], [27], [28], [29] from single or multiple images. Other works show learning implicit representations for objects is a promising avenue [1], [2], [30], [31], [32], [33], [34], [35], [36]. For example, IDR [5] and DVR [4] take advantage of differentiable rendering formulation for implicit shape and texture representations and show the possibility of recovering smooth surfaces for objects with rich textures from a set of posed images. They cannot handle many real-world cases, such as big items with flattened areas (e.g., furniture). Besides, they fall into the neural rendering category, thus would also benefit from the lighting transfer avenue.

To the best of our knowledge, no high-performing solution can automatically reconstruct perfect meshes and their UV texture atlases for real-world objects. Moreover, even if we can obtain an ideal 3D model with a perfect topology, we also need to rebuild its UV textures and materials. Unfortunately, texture and material recovery are currently receiving relatively poor attention, and the progress is not smooth.

B. Neural Rendering Leveraging NeRFs

Recent advances show neural fields representations are promising to describe scenes, and support rendering photo-realistic images of the fitted scenes under desired viewpoints [6], [37], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49],...
LighTNet aims to transfer the lighting details from an imperfect shading map $S'$ to the corresponding image $I_s$. It reasons about the reformulated image composition model $I_t = (D + R + \alpha) \cdot (S' + S'_r)$. The yellow (left) part shows the $\langle R3DM, 3DM \rangle$ pairs generation process, and is only included in the training process. Once optimized, LighTNet can be used for any newly created 3D scenes with both seen and unseen R3DMs and support free lighting simulation. In the inference phase, $I_s$ of an object is the 2D instance synthesized by a trained NeRF or any other high-performing free view synthesis formulations (See Figs. 1 and 4).

For example, they can only synthesize local shadows caused by self-occlusion of its optimized single scene (or object). In fact, they have not considered compositing individual NeRFs to freely create and edit 3D scenes, thus have not handle the possible indirect lighting effects caused by objects interaction. We refer to the “Discussion” section for more explanation about the differences.

### III. LIGHTING TRANSFER NETWORK (LIGHTNET)

As shown in Fig. 2, the goal of LighTNet is to transfer the lighting details from an imperfect shading map $S'$ to the corresponding image $I_s$. We will start with a brief introduction to the simplified image composition formulation in Section III-A, which is the theoretical basis of LighTNet. Then, we explain the network architecture in Section III-B. Finally, in Section III-C, we introduce the proposed Lab Angle Loss and other involved objectives.

**A. Preliminaries: Image Composition**

An image can be expressed as the point-wise product between its shading $S$ and albedo $A$, i.e., $I = A \cdot S$, as discussed in [59], [60], [61], [62]. $A$ is often simplified as a diffuse map which shows the base colors and textures used in materials with no lighting information. However, the render equation [63] in general physically-based renders tells us $A$ should encode other material properties such as refraction and specularity. We follow the compositing process and definitions in V-Ray [13] and simplify its formulation as

$$I = D \cdot S + R \cdot R_l + \alpha_2,$$

(1)
where \( D \) is the diffuse map, \( S \) is all the raw lighting (both direct and indirect) in the scene and we regard it as “Shading” in this paper, \( R \) defines the strength of the reflection of the materials, \( R_l \) stores reflection information calculated from the materials’ reflection values in the scene, and \( \alpha_2 \) provides the interactive effects between other material properties and lighting. \( S \) encodes the per-pixel lighting of a scene, we approximate \( R_l \) via \( S + \alpha_1 \). Going a further step, we find that rendering the supervision information \( S + \alpha_1 \) and \( \alpha_2 \) is impractical because we only have a rough geometry R3DM. Besides, learning them separately would increase our framework complexity. We thus further simplify the formulation as

\[
I = (D + R + \alpha) \cdot S
\]

by regarding \((R \cdot \alpha_1 + \alpha_2)/S\) as a packed residual effect \( \alpha \).

B. Architecture

Our lighting transfer network (LighTNet) is developed based on the formulation \( I = (D + R + \alpha) \cdot S \). Given a training sample \((I_s, S', I_t, D, R)\), where \( I_t, D, \) and \( R \) are the ground-truth images, LighTNet takes \( I_s \) and \( S' \) as inputs, and target at reconstructing \( I_t \). See Section V-A for details about the training samples capturing process.

We utilize an encoder-decoder network \( E \) to estimate both the diffuse map \( D \) and the reflection strength \( R \) from \( I_s \). We learn \( R \) and \( D \) in a supervised manner using:

\[
L_{DR} = |R - R'| + |D - D'|.
\]

After that, the remained major issue is that the shading \( S' \) is not smooth since its R3DM’s surfaces are uneven. We know that shading is determined by surface normal and illumination [61]. We clarify \( D \) and \( R \) mapping from \( I_s \) usually imply smooth normal information that could remedy \( S' \). Towards the purpose, we obtain an intermediate representation by concatenating \( S' \), \( D \), and \( R \) together, and take an encoder network \( E_r \) to map it to a feature \( F_r \). With \( F_r \), a straightforward option is to directly predict a smooth shading \( S \). In our experiments, we find a smoother \( S \) could be captured following \( S = S' + S'_r \), where \( S'_r \) is the learned residual from \( F_r \) via a decoder network \((D_s)\).

Finally, as analyzed before, the model \( I = (D + R) \cdot S \) cannot describe the full lighting effects. Especially, our experiments in Fig. 7 show it cannot well preserve shadows. We thus follow (2) to directly predict a residual effect \( \alpha \) from \( F_r \) through another decoder network \((D_s)\). Considering all above, the target image can be composited as

\[
I_t = (D + R + \alpha) \cdot (S' + S'_r).
\]

C. Objectives

In previous relighting efforts, the \( L1 \) photometric loss \( L_{L1} \) \((||I_t - I_s|| \text{ or } ||\log I_t - \log I_s||)\) was commonly used as a major term to preserve the basic image content in the reconstruction process [65], [66], [67]. However, we find in our experiments it will degrade the lighting transfer ability of LighTNet as shown in Fig. 9. A possible reason is that it pushes the learning procedure to focus more on reducing the color differences instead of local lighting discrepancies. We thus propose to minimize the following losses that are closely related to perceptual quality and lighting effects.

**Feature Reconstruction Loss:** The feature reconstruction loss [68] encourages \( I_t \) to be perceptually similar to \( I_s \) based on matching their semantic features. We take VGG-19 [69] pretrained on ImageNet [70] as the feature extractor \( \phi \) and denote \( \phi_j(x) \) as the output of the \( j \)th convolution block. The feature reconstruction loss is expressed as:

\[
L_{FR} = \frac{1}{C_j \cdot H_j \cdot W_j} \sum_{c, h, w} ||\phi_j(I_t) - \phi_j(I_s)||,
\]

where \( C_j \cdot H_j \cdot W_j \) is the feature dimensions of \( \phi_j(x) \). In this paper, we utilize activations of the third convolution block \((j = 3)\) to compute \( L_{FR} \).

**Structural Dissimilarity:** SSIM [71] is another perceptual-motivated metric that measures structural similarity between two images. We take the structural dissimilarity (DSSIM) as a measure following the success in [72]:

\[
L_{DSSIM} = \frac{1 - \text{SSIM}(I_t, \bar{I}_t)}{2},
\]

**Lab Angle Loss:** We find that LighTNet optimized with aforementioned loss terms would produce images with darker global brightness as shown in Fig. 9. A possible reason is that \( L_{FR} \) and \( L_{DSSIM} \) only enhance local perceptual quality while overlooking the lighting contrast. In the paper, we thus propose a novel Lab Angle loss to consider the pixel-wise ratio between lighting strength and colors as:

\[
L_{Lab} = \frac{1}{H \cdot W} \sum_{h, w} \arccos \left( \frac{\langle \phi(I_t)(h, w), \phi(I_s)(h, w) \rangle}{\|\phi(I_t)(h, w)\| \cdot \|\phi(I_s)(h, w)\|} \right),
\]

where \( \langle x, y \rangle \) denotes the inner product of vector \( x \) and \( y \), \( \phi(\cdot) \) represents the RGB to \( Lab \) converter, \((h, w)\) is the spatial location, and \( H \times W \) is the image size.

**Full Objective:** Our LighTNet is optimized in an end-to-end fashion with the objective:

\[
L = L_{DR} + \lambda_1 L_{FR} + \lambda_2 L_{DSSIM} + \lambda_3 L_{Lab},
\]

where the loss weights \( \lambda_1, \lambda_2, \) and \( \lambda_3 \), in all the experiments, are set to 0.05, 0.5, and 0.5, respectively.

IV. RENDERING WITH LIGH TNET AND R3DMs

In this section, we show how a trained LighTNet and R3DMs can be flexibly integrated into practical 3D modeling workflows such as 3D scene creation and rendering. For example, we are interested in a real yellow chair, as shown in Fig. 4. Given its reconstructed R3DM and neural fields representation (NeRF [6] in this paper), we can create a 3D scene by putting the yellow chair’s R3DM and some 3DMs into a 3D room. Here, both the room and the involved 3DMs have not been seen before. To showcase the scene, we would like to render a high-quality image, in which the involved 3D models are with rich lighting details. Towards the goal, we can set a high-energy light source,
We can represent real-world objects as individual NeRFs and R3DMs, and freely composite them to create unlimited 3D scenes. After lighting editing by artists, LighTNet can transfer direct and indirect lighting effects on R3DMs (e.g., $S'$) to the corresponding NeRF instances (e.g., $I_s$). See Section IV for the detailed explanation.

We take the “Sofa” case as an example to show how to capture a training sample $\{I_s, S', \bar{I}_t, \bar{D}, \bar{R}\}$ via 3D CAD models and 3D scenes. The elements are rendered by Blender [64]. LighTNet is trained once on the 3DF-Lighting training set, and can be used for all the newly created scenes with both seen and unseen R3DMs and arbitrary lighting.

and render a scene image $I_{PBR}$, a shading $S'$, and an object’s mask $M$, under a good viewpoint. Simultaneously, we synthesize an image $I_s$ with the same camera pose via NeRF. Then, we are able to capture a target image $I_t$ by transferring lighting from $S' \cdot M$ to $I_s \cdot M$ via the trained LighTNet model. Finally, we replace $I_{PBR} \cdot M$ with $I_t \cdot M$ to obtain the final photo-realistic rendering $I_R$. The complete process can be formulated as:

$$I_R = I_{PBR} \otimes (1 - M) + M \otimes \text{LighTNet}(I_s, S'),$$

(9)

where $\otimes$ is the element-wise production operation. In practice, there will be some regions in boundary areas that cannot be covered by $I_t$. We directly fill these regions via a SOTA image inpainting technique [73]. Some qualitative results are shown in Fig. 11.

V. EXPERIMENTS

In this section, we conduct many experiments to examine the lighting transfer avenue. We first present the training and evaluation sets building processes in Section V-A. Then, we build several baselines and make benchmark comparisons with them in Section V-B. Finally, we perform various ablation studies to discuss our method in Section V-C.

A. Datasets

1) 3DF-Lighting Training Set: The training set construction pipeline is illustrated in Fig. 5. We take 50 3D scenes and the involved 30 3D CAD models (denoted as 3DMs) in 3DFront [76] to construct the training set. First, we need to recover these objects’ rough 3D meshes (R3DMs). We simply adopt the mesh subdivision algorithm [77], [78] to densify the CAD models’ surfaces, then add random noise to each vertex.
Second, for a specific object in a scene, we simulate uniform sunlight to the scene, randomly choose a viewpoint and render the object’s diffuse map $\mathcal{D}$, reflection strength $\mathcal{R}$, and color image $\mathcal{I}_t$. Third, we randomly change the light source’s position and increase the lighting energy to capture a target image $\mathcal{I}_t$. Finally, we render the rough shading $\mathcal{S'}$ by replacing the object’s 3DM as its R3DM. Following the pipeline, we can construct a training set $\{(\mathcal{I}_t, \mathcal{S'}, \mathcal{I}_t, \mathcal{D}, \mathcal{R})\}$. This paper takes Blender [64] with V-Ray plug-in as the render engine to secure these elements. We have also rendered $\mathcal{I}_t$ to maintain consistency between training and inference. As reported in Table I, the “NeRF” setting (LightTNet) yields similar scores compared to the “Blender” setting (LightTNet).

**Evaluation Set:** We build a test set using another 10 furniture shapes and 20 3D scenes from 3D-FRONT. We take one object as an example to present the test set building process. We randomly render 200 images from viewpoints sampled on a full sphere to learn its NeRF and R3DM. For each 3D scene, we put the object’s R3DM into the scene and randomly render thirty $\mathcal{S'}$ and $\mathcal{M}$. Simultaneously, we synthesize the corresponding thirty $\mathcal{I}_t$ using its NeRF. Finally, we render the thirty $\mathcal{I}_t$ (ground truth images) at size 800 $\times$ 800 by replacing the R3DM with its 3DM. Each 3D scene’s light source and energy are pre-defined. Through the workflow, we construct a test set with 6,000 samples $\{(\mathcal{I}_t, \mathcal{S'}, \mathcal{I}_t, \mathcal{M})\}$. We pre-assign V-Ray materials to each 3D model (R3DM and R3D) manually.

2) **Generalizing to Real-Lighting:** We also conduct qualitative evaluation on a real dataset named Real-Lighting. Specifically, we capture some object-centric videos via a mobile phone, and reconstruct these objects via NeRF. We create some 3D scenes using these objects’ R3DMs and other 3DMs. Some rendered images of these scenes are presented in Fig. 11. We can see the lighting details have been successfully preserved. The LightTNet model is trained only on the 3DF-Lighting training set. All the scenes and objects in Real-Lighting have not been seen previously.

Moreover, we choose two individuals from the ActorsHQ [79] dataset and incorporate two real-world 360 scenes from Mip-NeRF 360 [51] for our experiment. Using Instant-NGP [80], we reconstructed the two individuals, and for the two scenes, we employed MipNeRF 360 [51]. Subsequently, we integrated the digital representations of the individuals and objects into the reconstructed 3D scenes, forming new composite 3D scenes. Light sources were randomly placed in these new 3D scenes. That means, all the content in the new scenes are reconstructed. The qualitative results, depicted in Fig. 12 and the accompanying video, highlight the adaptability of our method to both human subjects and reconstructed real-world 3D scenes.

**B. Benchmark Comparisons**

**Building Baselines:** We build baselines by reformulating three works, including Pix2Pix [74], DPR [75], and SS-VBRDF [67], to study the lighting transfer setting. Our research addresses a novel problem arising from the practical 3D house design and rendering workflow. With the proposed lighting transfer pathway depicted in Fig. 1, our objective is to transfer lighting details from the “Shading” map ($\mathcal{S'}$) to the NeRF rendering ($\mathcal{I}_t$) (refer to Fig. 4). While we accomplish this task through an image composition formulation based on the V-Ray render engine’s compositing process, it can also be viewed as a conditional image-to-image translation problem. Hence, Pix2Pix [74] is selected as one of our baselines. We learn the mapping from $\mathcal{I}_t \oplus \mathcal{S'}$ to $\mathcal{I}_t$, where $\oplus$ is the concatenate operation along the channel dimension. Considering DPR [75] and SS-VBRDF [67], they belong to the realm of inverse rendering, predicting BRDF from single images and supporting image relighting. To decompose BRDF, they require predicting lighting (usually environment lighting or spherical harmonics) for a given single image. Consequently, we can integrate them into the proposed lighting transfer avenue by directly rendering the scenes’ spherical harmonics lighting through PBR and using it directly in the relighting process. All the methods (including LightTNet) have been trained on the 3DF-Lighting train set.

**Performance:** To measure the lighting synthesis ability, we take $L_1$-Norm, PSNR, SSIM [71], and our $\text{Lab Angle}$ loss as the metrics. From the scores presented in Table I, our LightTNet outperforms the compared methods by a large margin. Especially, while the best PSNR and $L_1$-Norm obtained by the baselines are 26.65 and 0.0345, LightTNet significantly improves them to 30.17 and 0.0219. It is not surprising since (1) DPR and SS-VBRDF focus more on modeling global illumination, and (2) transferring lighting from shading with uneven surfaces is more challenging. Several qualitative comparisons are reported in Fig. 6. LightTNet achieves realistic relighting results with impressive shadow details. In Fig. 11, we illustrate some further examples of our approach generalizing to real objects, using the LightTNet model only trained on 3DF-Lighting.

| Method       | $L_1$-Norm $\downarrow$ | PSNR $\uparrow$ | SSIM $\uparrow$ | $\text{Lab Angle} \downarrow$ |
|--------------|-------------------------|-----------------|-----------------|-------------------------------|
| Pix2Pix [75] | 0.0345                  | 26.65           | 0.9042          | 0.4314                        |
| DPR [76]     | 0.0399                  | 25.39           | 0.8692          | 0.4576                        |
| SS-VBRDF [68]| 0.0373                  | 26.02           | 0.9040          | 0.3796                        |
| LightTNet    | 0.0219                  | 30.17           | 0.9142          | 0.3137                        |
| LightTNet$^1$| 0.0281                  | 29.93           | 0.9203          | 0.3173                        |

We use the proposed lab angle distance and several widely studied metrics, including $L_1$-Norm, PSNR, and SSIM [71], to measure a method’s lighting transfer ability. LightTNet and LightTNet$^1$ denote training LightTNet with Blender and NeRF images, respectively (refer to Section V-A).

**TABLE I QUANTITATIVE EVALUATION ON 3DF-LIGHTING**

We argue that a slight numerical gain over the studied metrics may imply an improved visual experience since lighting is a detailed effect. We refer to the supplemental material, available online, for more qualitative comparisons.

**Objectives:** We discuss the objectives presented in Section III-C based on our lighting transfer formulation (4). We take $\mathcal{L}_{FR}$ as the baseline, and incorporate other objectives one by one. $\mathcal{L}_{DR}$ is used in all the experiments. From Table II, there is a remarkable gap between $\mathcal{L}_{L1}$ and $\mathcal{L}_{FR}$. Bringing in $\mathcal{L}_{DSSIM}$...
Fig. 6. Qualitative comparisons on 3DF-Lighting. We make qualitative comparisons with the reformulated Pix2Pix [74] and SSVBRDF [67]. LighTNet achieves realistic relighting results with impressive shadow details. $I_s$ and $S'$ are rendered by NFR and PBR, respectively.

Table II

| Objective | Metric |
|-----------|--------|
| $L_{FR}$ | $L_{DSSIM}$ | $L_{Lab}$ | $L_{L1}$ | L1-Norm ↓ | PSNR ↑ | SSIM ↑ | Lab Angle ↓ |
| √ | √ | √ | √ | 0.0277 | 28.37 | 0.8774 | 0.3551 |
| 0.0254 | 29.06 | 0.9006 | 0.3717 |
| √ | √ | 0.0229 | 29.83 | 0.9129 | 0.3317 |
| 0.0219 | 30.17 | 0.9142 | 0.3137 |
| √ | √ | 0.0240 | 29.37 | 0.9142 | 0.3426 |

We find that optimizing LighTNet with a $L_{L1}$ photometric loss ($L_{L1} = |I_t - \bar{I}_t|$) would yield a degenerate performance.

Table III

| Variant | L1-Norm ↓ | PSNR ↑ | SSIM ↑ | Lab Angle ↓ |
|---------|-----------|--------|--------|-------------|
| $D \cdot S$ | 0.0283 | 28.46 | 0.9128 | 0.3449 |
| $(D + R) \cdot S$ | 0.0262 | 28.83 | 0.9117 | 0.3411 |
| $(D + R) \cdot S + \alpha$ | 0.0238 | 29.45 | 0.9064 | 0.3458 |
| $(D + R + \alpha) \cdot S$ | 0.0219 | 30.17 | 0.9142 | 0.3137 |

Composition Formulations ($S = S' + S'_r$)

| Architecture: Learning $S'_r$ or Not | L1-Norm ↓ | PSNR ↑ | SSIM ↑ | Lab Angle ↓ |
|--------------------------------------|-----------|--------|--------|-------------|
| $(D + R + \alpha) \cdot S'$ | 0.0260 | 28.70 | 0.8935 | 0.3574 |
| $(D + R + \alpha) \cdot S^*$ | 0.0241 | 29.35 | 0.8996 | 0.3473 |
| $(D + R + \alpha) \cdot (S' + S'_r)$ | 0.0219 | 30.17 | 0.9142 | 0.3137 |

$S^*$ means that we directly predict a smooth shading from $F_r$ instead of estimating the shading residual $S'_r$.

Yields a notable improvement overall. In further, although $L_{Lab}$ only provides a slight PSNR gain (+0.34), it does enhance the lighting effects as reported in Fig. 9. It is worth mentioning that optimizing LighTNet with an auxiliary $L_{L1}$ loss would largely degrade L1-Norm (−0.021) and PSNR (−0.8). See Fig. 9 for a qualitative evaluation.

Image Composition Formulations: In Table III (Top), we study the image composition variants discussed in Section III-A. Overall, our revised formulation $(D + R + \alpha) \cdot S$ outperforms the baseline $D \cdot S$ by a significant margin. From the first three columns, while $R$ supplements reflection effects, the residual $\alpha$ is important in encoding other lighting effects. By investigating $(D + R + \alpha) \cdot S$ versus $(D + R) \cdot S + \alpha$, we find that it would be much better to simulate the PBR compositing process following the product manner. Some qualitative comparisons are shown in Fig. 7.

Learning $S'_r$ or Not? In (4), we choose to learn a residual $S'_r$ to remedy the uneven surfaces of $S'$. There is an alternative that directly estimates a smooth shading $S^*$ from $F_r$. As presented in Table III (Bottom), while $(D + R + \alpha) \cdot S^*$ improves $(D + R + \alpha) \cdot S'$ by 0.65 on PSNR, our residual architecture significantly yields a PSNR gain of 1.47.
Fig. 7. We qualitatively evaluate the lighting transfer ability of the image composition variants. \((\mathcal{D} + \mathcal{R}) \cdot (S' + S'_{\alpha})\) would be a much better choice for simulating the PBR compositing process.

**Smoothness of R3DMs:** In Fig. 10, we explore the impact of the smoothness of R3DMs on the final rendering quality. It is not supersizing that if a method can recover smoother surfaces (e.g., NeuS), LightTNet would perform better. For the “extremely noisy surfaces” case, LightTNet fails to render the lighting details and cannot address the uneven artifacts. The reasons are: (1) a PBR system cannot produce a correct shading map for extremely noisy meshes, as the lighting effects are closely related to surface normals; (2) The capability of LightTNet is not sufficient to remedy these very worst typologies.

**Weights for Loss Terms:** Here, we simply study \(\lambda_1 \mathcal{L}_F + \lambda_2 \mathcal{L}_{DSSIM} + \lambda_3 \mathcal{L}_{Lab}\) through a controlled variable technique. The scores are reported in Fig. 8. For efficiency, this ablation was performed on a reduced subset (1/5) of 3DF-Lighting.

VI. DISCUSSION

**Setting:** Our primary insight of develop such a lighting transfer avenue is inspired by the industry production pipeline. For example, in order to showcase furniture online, a furniture seller typically needs artists to reconstruct 3D CAD models of their furniture. Subsequently, designers use these 3D furniture models to create a virtual 3D CAD scene, and a rendering engine is employed to generate images and videos that effectively showcase the furniture. Crafting high-quality 3D furniture models is a costly endeavor, especially when dealing with unique materials or styles. Moreover, achieving high-quality furniture reconstructions requires the expertise of professional artists. With the motivation, we focus on how to flexibly integrate automatically reconstructed 3D models into practical 3D modeling workflows.

Essentially, with the proposed lighting transfer avenue, one can import newly reconstructed Rough 3D Models (R3DMs) into graphical software (e.g., 3DS-Max). This allows users to design diverse indoor and outdoor 3D scenes and collaboratively render content alongside other high-quality 3D CAD models (3DMs). It’s noteworthy that NeRF in our paper serves as a specific example to illustrate the potential of the lighting transfer avenue. In our approach, the R3DM component is independent of the Neural Fields Rendering (NFR) synthesis (or NeRF) segment.
Fig. 9. We qualitatively discuss the objectives in Section III-C. $L_{FR} + L_{DSSIM}$ yields a notable improvement in dealing with uneven shading surface and local shadows compared to $L_{L1}$. $L_{Lab}$ could further enhance the lighting effects.

For a real object, we can employ one method to reconstruct its R3DM and another method for 2D instance synthesis if it outperforms NeRF in novel view synthesis.

Relation to Inverse Rending With Implicit Neural Representation: Leveraging implicit neural representation, recent inverse rendering works can decompose a scene under complex and unknown illumination into spatially varying BRDF material properties [11], [12], [56], [57], [58]. These techniques enable material editing and free view relighting of the reconstructed scene. Here, we take NeRFactor [12] as an example to discuss the main differences of these works and the raised lighting transfer avenue. First, NeRFactor focused on estimate SVBRDF properties of single scene or object. Beyond free-view relighting, we can imagine that NeRFactor supports the object inserting application, i.e., inserting a 3D object into a static image, as we can extract the global lighting probes from the target static image. But if we would like to insert multiple 3D objects into a single image, NeRFactor would overlook the possible indirect lighting effects caused by object-to-object occlusion because there is no a “3D scene” concept involved. It’s worth mentioning NeRFactor can simulate local shadows caused by self-occlusion of its reconstructed single object. In contrast, we study a more practical problem that is “can we use rough 3D models, together with 3D CAD models drawing by artists, to create arbitrary 3D scenes and render high-quality contents?” Thereby, our studied setting is totally different from the setting of NeRFactor. Second, in the proposed lighting transfer avenue, the R3DM part is independent with the NFR synthesis part. For a real object, we can use a method to reconstruct its R3DM, and use another method to perform 2D instance synthesizing. This paper takes NeRF as an example to explain the proposed avenue because: (1) it supports high-quality novel view synthesis; and (2) at the same time, we can conveniently extract a R3DM from a trained NeRF via a marching cube algorithm. From this perspective, we can apply NeRFactor instead of NeRF for 2D instance synthesizing. But as analyzed before, how should we handle the indirect lighting details caused by the interaction of multiple 3D objects? The introduced LighTNet could give a possible answer to this question.

VII. LIMITATION

Tough Materials: LighTNet cannot handle strong specular materials yet. As shown in Fig. 13, the synthesized 2D instances by NeRF contain the reflected content. It’s unavoidable yet as NeRF series learn to fit a captured scene for its free view synthesis. We find LighTNet would preserve the reflected content while ignoring the real reflected content of the newly created scenes. A possible reason is that we do not have strong specular materials in our training set, as 3D-FRONT only shared several specular objects. It should be one of the major limitations. This issue would disappear if future NeRF research or other view synthesis works can disentangle the reflected content from the objects’ textures. Moreover, our approach struggles with scattering materials (e.g., clouds) and objects with intricate structures (e.g., Eiffel Tower). The current methodology falls short in recovering the meaningful geometry of these categories, resulting in a “Shading” map riddled with considerable noise.
Fig. 11. Generalizing to real-lighting. We reconstruct some real objects and use them to create some scenes. See Section V-A for an introduction. Bottom: We put the reconstructed objects to different 3D scenes. Here, NeRF means the 2D instance synthesized by NeRF. The lighting details have been successfully preserved by our LightTNet. Please see the shadows caused by object-to-object interactions. Note that, LightTNet here is only trained on the 3DF-Lighting training set. We refer to the supplementary for some rendered videos.
We initially reconstruct the scenes, persons, and objects using NeRF approaches and subsequently utilize the reconstructed elements to compose new scenes. For a comprehensive view of the 360 lighting effects, please refer to the supplementary video, available online.

**Fig. 13. Failure case.** One of the major limitations of LighTNet is it cannot handle strong specular materials. The reflected content would be incorrectly maintained during the rendering process. Zoom in for a better view.

**Blurriness & Dark Spots:** Our renderings exhibit slight blurriness compared to ground truth (GT) images and contain artifacts such as dark spots. Regarding the blurriness, it’s reasonable to expect that images generated by a standard CNN, like our composition network, may not seamlessly match the quality of those rendered by advanced rendering engines. As for the artifacts, it’s possible that the “shading residual” approach, while performing better than the compared image composition variants in Fig. 7, may not fully address the issue of uneven surfaces. We suggest that further investigation into techniques in super-resolution and diffusion models could address these challenges.

**Rendering Speed:** Presently, rendering an image using our method on a V100 GPU takes approximately 4 seconds. Thereby, our approach only support off-line rendering at this time. As a complement, training LighTNet on 3DF-Lighting requires approximately 12 hours utilizing a single V100 GPU. To speed up the rendering process, the UNet structure might be deeply revised and optimized.
Stability for Video Rendering: Another limitation is that our approach currently encounters stability issues in video rendering, as we have focused solely on rendering static images in this paper. To quantitatively evaluate stability, we constructed a 360-degree test set using six furniture shapes and twelve 3D scenes from 3D-FRONT. Initially, we pre-defined a light source and energy for each scene, randomly rendering 200 images from viewpoints sampled on a full sphere to train NeRF and extract its R3DM. Subsequently, we placed the object’s R3DM into the scene, generated a random light source and energy for each 3D scene, and rendered 100 $S'$ and $M$ from viewpoints uniformly sampled on a semi-sphere around the object’s R3DM. Simultaneously, we synthesized the corresponding 100 $I_s$ using its NeRF. Finally, we rendered the 100 $I_t$ (ground-truth images) at size 800 $\times$ 800 by replacing the R3DM with its 3DM. Through this workflow, we constructed a 360-degree test set with 600 samples ($I_s$, $S'$, $I_t$, $M$). As reported in Table IV, although LighTNet outperforms Pix2Pix [74] in all metrics, the variances of $L1$-Norm and PSNR are larger than Pix2Pix [74]. It makes sense since the final rendering of Pix2Pix consistently contains weak lighting effects. Modeling the temporal consistency for LighTNet would be a promising avenue for future research to overcome this limitation.

### VIII. Conclusion

In this paper, we are prudent to rethink reconstructed rough 3D models (R3DMs) and present a lighting transfer avenue to flexibly integrate R3DMs into practical 3D modeling workflows such as 3D scene creation, lighting editing, and rendering. Physically-based rendering (PBR) would render low-quality images of scenes constructed by R3DMs. A remedy is to represent real-world objects as individual neural fields (e.g., NeRF) in addition to R3DMs, as neural fields rendering (NFR) can synthesize photo-realistic object images under desired viewpoints. The main question is that NFR instances cannot reflect the lighting details on R3DMs. We thus present a lighting transfer network (LighTNet) as a solution. LighTNet reasons about a reformulated image composition model and can bridge the lighting gaps between NFR and PBR, such that they can benefit from each other. Moreover, we introduce a new $Lab$ angle loss to enhance the contrast between lighting strength and colors. Qualitative and quantitative comparisons show the superiority of LighTNet in preserving both direct and indirect lighting effects.

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