# **NeRFReN: Neural Radiance Fields with Reflections**

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### **Abstract**

Neural Radiance Fields (NeRF) has achieved unprecedented view synthesis quality using coordinate-based neural scene representations. However, NeRF's view dependency can only handle simple reflections like highlights but cannot deal with complex reflections such as those from glass and mirrors. In these scenarios, NeRF models the virtual image as real geometries which leads to inaccurate depth estimation, and produces blurry renderings when the multi-view consistency is violated as the reflected objects may only be seen under some of the viewpoints. To overcome these issues, we introduce NeRFReN, which is built upon NeRF to model scenes with reflections. Specifically, we propose to split a scene into transmitted and reflected components, and model the two components with separate neural radiance fields. Considering that this decomposition is highly under-constrained, we exploit geometric priors and apply carefully-designed training strategies to achieve reasonable decomposition results. Experiments on various self-captured scenes show that our method achieves highquality novel view synthesis and physically sound depth estimation results while enabling scene editing applications. Code and data will be released.

# 1. Introduction

Photorealistic novel view synthesis (NVS) from unstructured image collections is crucial to creating immersive virtual experiences. Despite having achieved significant progress in controlled settings, challenges still exist in handling light transport at the surface of different materials. For example, reflections caused by glass or mirrors commonly exist in real-world scenes, posing great difficulties for novel view synthesis due to the severe view-dependent effects.

Neural Radiance Fields (NeRF) [13], as an emerging technique in this field, has achieved impressive view synthesis quality by adopting volumetric representations with coordinate-based neural networks. By conditioning radi-

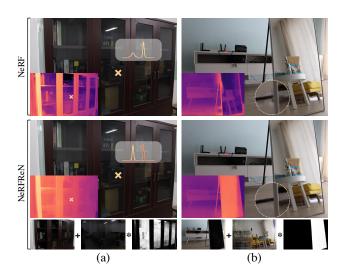


Figure 1. NeRF models the stable reflection image as real geometries rather than view-dependent effect of the points on the reflective surface. We illustrate two problems NeRF may encounter when modeling scenes with complex reflections: (1) inaccurate depth estimation in reflective regions ((a) and (b)); (2) inaccurate rendering when the multi-view consistency is violated (magnified areas in (b)). NeRFReN tackles these problems by modeling the transmitted and reflected component of the scene with separate NeRFs, and synthesizing views in the image domain (bottom). See Sec. 3.1 for more detailed analysis.

ance on both coordinates and viewing directions, NeRF is able to handle view-dependent effects like highlights faithfully. However, in the presence of severe reflections that contain a stable virtual image other than highlights, NeRF tends to model the scene geometry behind the reflective surface as translucent (like fogs) and regard the reflected geometries as appearing at some virtual depth.

The reason is that NeRF does not explain the view-dependency of a reflecting surface point by changing the color of this very point when viewed from different directions, but explain it by utilizing all the spatial points behind it along the camera ray to get the correct color through volume rending as in Eq. (2), resulting in foggy geometries and physically wrong depth. Although this works well for view synthesis in certain scenarios, there are two inherent limita-

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tions: (1) it is hard to estimate the correct scene geometry, preventing it from further explanations or editing; (2) inaccurate renderings are generated when the multi-view consistency does not hold since the reflected objects may only be seen in some of the images, which limits the views NeRF can correctly synthesize.

To this end, we propose NeRFReN, which enhances **NeRF** to handle scenes with <u>Re</u>flectio<u>N</u>s. Instead of representing the whole scene with a single neural radiance field, we propose to model the *transmitted* and *reflected* parts of the scene with separate neural radiance fields. To synthesize novel views, the transmitted image  $I_t$  and reflected image  $I_r$  rendered by the corresponding fields are composed in an additive fashion, where the reflected image  $I_r$  is weighted by a learned *reflection fraction map*  $\beta$ :

$$I = I_t + \beta I_r \tag{1}$$

However, it is highly under-constrained to decompose the scene into transmitted and reflected components in an unsupervised way. There are infinitely many solutions that could lead to correct renderings on training images. Common degradations are (1) having one of the components explain the full scene while leaving the other empty; (2) two components both model the full scene; (3) somewhere between (1) and (2), where part of the one component is mixed into the other one, resulting in incomplete transmitted/reflected geometry. To solve the ambiguities, we made the following assumptions:

- **Assumption1:** the reflection fraction is only related to the transmitted component, since it indicates the material of the reflecting surface;
- Assumption2: the transmitted component has a locally smooth depth map, since most of the reflectors in real world scenes are almost planar;
- Assumption3: the reflected component requires only simple geometry to present correct renderings since most of the time we can only see the reflection image from very limited viewing directions.

Accordingly, we design a specific network architecture for Assumption1, apply a depth smoothness prior for Assumption2, and a novel bidirectional depth consistency constraint for Assumption3. Together with our warm-up training strategy, we are able to faithfully decompose the transmitted and reflected components, achieving promising novel synthesis results on various real-world scenes. As for even more challenging cases (such as mirrors) in which the ambiguities cannot be solved by these assumptions, we exploit an interactive setting where a small number of user-provided reflection masks can be utilized to get the correct decomposition (Fig. 4, tv and mirror).

To summarize, our contributions are:

- We analyze NeRF's behavior and limitations in modeling reflective regions, and propose to use separate transmitted and reflected neural radiance fields for scenes containing complex reflections.
- We devise specific network architectures, exploit geometric priors, and apply carefully-designed warm-up training strategy, to achieve physically sound decomposition results with competitive novel view synthesis quality compared to vanilla NeRF on several self-captured scenes, including challenging cases like scenes with mirrors.
- We also investigate depth estimation and scene editing as further applications based on the decomposed results.

#### 2. Related Work

#### **Neural Scene Representations for Novel View Synthesis**

Novel view synthesis aims to generate images observed from novel views based on a set of captured images of the scene. In order to get correct synthesis results, the underlying 3D geometry of the scene must be taken into consideration, for which various scene representations are proposed. Image-based rendering [3,7,15,16,23,25] mainly utilizes a mesh model of the scene, which is usually reconstructed from offline Structure-from-Motion (SfM) and Multi-View-Stereo (MVS) methods [17,18]. Other commonly adopted representations include voxel grid [21], volume [10], point cloud [1] and multi-plane images [5,28].

In recent years, coordinate-based neural representations [4, 12–14, 22] have shown remarkable capability of modeling the 3D world. Among them, Neural Radiance Fields (NeRF) [13], as an emerging technique in the novel view synthesis domain, models the scene as a continuous volumetric field parameterized by neural networks. NeRF produces astonishing novel view synthesis results in several casually-captured real scenes, even when view-dependent effects like highlights present. Our work extends NeRF to support view synthesis in scenes with reflected objects coming from glass and mirrors, which are common in real-world scenes and strongly affect the immersion of people in virtual experiences.

Reflections in Rendering Reflections are common in real world, but can be hard to correctly model without simulating the light paths using techniques like ray-tracing. In computer graphics, Screen Space Reflection (SSR) technique is developed to simulate the reflection effects with low costs. Synthesizing novel views in scenes with reflections has long been a challenging problem, but is rarely explored [19,29]. Sinha *et al.* [19] for the first time targets at novel view synthesis in scenes with reflections using imagebased rendering. They propose to decompose each image into a transmitted layer and a reflected layer combined with a binary reflection mask. They approximate the geometry of

each layer as piece-wise planar surfaces, and estimate their depth by two-layer stereo matching. The reflection mask is optimized using graph cut based on depth uncertainty.

Our work adopts similar image formulation as Sinha et al. [19], but models the scene with NeRF for its state-of-the-art performance on the novel view synthesis task. NeRF resolves view-dependency by taking the viewing direction as network input, but is only able to model low-frequency view-dependent effects. We extend NeRF by modeling the transmitted and reflected components with two separate neural radiance fields, and achieve visually appealing results in scenes with complex reflections.

#### 3. Method

Here we present NeRFReN, a neural radiance field approach for novel view synthesis in scenes with reflections. We first briefly recap the Neural Radiance Fields (NeRF) [13] in Sec. 3.1, and present our scene formulation and network architecture in Sec. 3.2. To faithfully decompose the scene into transmitted and reflected components, we exploit geometric priors (Sec. 3.3) and apply special training strategies (Sec. 3.4). Training with minimum user input to handle hard cases is described in Sec. 3.5.

#### 3.1. Neural Radiance Fields Revisited

Neural Radiance Fields (NeRF) represents a scene as a continuous volumetric field, where the density  $\sigma \in \mathbb{R}$  and the radiance  $\mathbf{c} \in \mathbb{R}^3$  at each 3D position  $\mathbf{x} \in \mathbb{R}^3$  under viewing direction  $\mathbf{d} \in \mathbb{R}^2$  are modeled by a multi-layer perceptron (MLP)  $f_{\theta} : (\mathbf{x}, \mathbf{d}) \to (\mathbf{c}, \sigma)$ , with  $\theta$  as learnable network parameters. To render a pixel, the MLP first evaluates points sampled from the camera ray  $\mathbf{r} = \mathbf{o} + t\mathbf{d}$  to get their densities and radiance, and then the color  $\mathbf{C}(\mathbf{r})$  is estimated by volume rendering equation approximated using quadrature [11]:

$$\widehat{\mathbf{C}}(\mathbf{r}; \sigma, \mathbf{c}) = \sum_{k} T_i(\sigma) (1 - \exp(-\sigma_i \delta_i)) \mathbf{c}_i$$
 (2)

where  $\delta_i = t_{i+1} - t_i$  and  $T_i(\sigma) = \exp(-\sum_{j < i} \sigma_j \delta_j)$ . Here  $\widehat{\mathbf{C}}$  is conditioned on  $\sigma$ ,  $\mathbf{c}$ , and T is conditioned on  $\sigma$  to simplify the description of our formulation in Sec. 3.2. We denote the contribution of a point to the cumulative color as its weight  $\omega_i$ :

$$\omega_i = T_i(\sigma)(1 - \exp(-\sigma_i \delta_i)) \tag{3}$$

NeRF is optimized by minimizing the following photometric loss:

$$\mathcal{L}_{nm} = ||\widehat{\mathbf{C}} - \mathbf{C}||_2 \tag{4}$$

The depth value  $t^*$  along the ray can be estimated by computing the expected termination depth [33]:

$$t^*(\mathbf{r};\sigma) = \sum_k \omega_i t_i = \sum_k T_i(\sigma) (1 - \exp(-\sigma_i \delta_i)) t_i \quad (5)$$

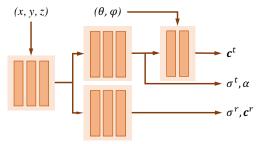


Figure 2. Network architecture of NeRFReN. The transmitted and reflected properties are predicted by separate branches of the network. Note that the reflection fraction value  $\alpha$  is predicted from the transmitted branch.

NeRF models view-dependent effects by taking viewing direction d as a network input. But as we will demonstrate in Tab. 1, the incorporation of d only enables NeRF to represent low-frequency view-dependent effects. Directly applying NeRF on scenes with severe reflections leads to a mixed geometry containing both the transmitted part and the reflected part of the scene, where the former is modeled as *translucent* to get correct view reconstructions. As illustrated on the first row of Fig. 1, the books in the bookcase appear to be "foggy", and the mirror surface is completely transparent.

The drawbacks are two-folds. First, depth estimation obtained by Eq. (5) can be highly inaccurate, staying somewhere between the real depth of the reflective surface and the virtual depth of the reflected image due to the existence of the translucent-like density field. In the gray box of Fig. 1(a) we visualize the weights of the points along the ray corresponding to the yellow cross. The weight distribution of NeRF appears to be bimodal, with the left peak contributed by the real surface points and right peak contributed by the virtual surface points. The depth along this ray is biased towards the virtual depth, visualized as a darker color in the depth map on the bottom left corner. Second, it is hard to get correct view synthesis results when the multiview consistency is violated. We illustrate this in Fig. 1(b), where some of the reflected objects can only be seen when front-facing the mirror. But as NeRF models the reflected objects as real geometries, we can still observe foggy contents seeing from the side of the mirror as shown in the magnified area.

## 3.2. NeRFReN

To better deal with scenes containing reflections, we propose to decompose a scene into a transmitted NeRF and a reflected NeRF. The transmitted field has density  $\sigma^t$  and radiance  $\mathbf{c}^t$ , and the reflected field has density  $\sigma^f$  and radiance  $\mathbf{c}^f$ . A reflection fraction value  $\alpha$  is learned for each 3D position to measure the reflection property of objects in different materials. To render the pixel along ray  $\mathbf{r}$ , we first render the two fields respectively to get  $\widehat{\mathbf{C}}(\mathbf{r}; \sigma^t, \mathbf{c}^t)$  and  $\widehat{\mathbf{C}}(\mathbf{r}; \sigma^r, \mathbf{c}^r)$ ,

where  $\widehat{\mathbf{C}}(\mathbf{r}; \sigma, \mathbf{c})$  is defined in Eq. (2). The reflection fraction  $\beta$  corresponding to the pixel is accumulated via volume rendering based on the geometry of the transmitted part:

$$\beta(\mathbf{r}; \sigma, \alpha) = \sum_{k} T_i(\sigma^t) (1 - \exp(-\sigma_i^t \delta_i)) \alpha_i \qquad (6)$$

The reflected color is attenuated by  $\beta$  and then composed with the transmitted color in an additive way to get the final pixel color:

$$\widehat{\mathbf{C}} = \widehat{\mathbf{C}}(\mathbf{r}; \sigma^t, \mathbf{c}^t) + \beta(\mathbf{r}; \sigma^t, \alpha) \widehat{\mathbf{C}}(\mathbf{r}; \sigma^r, \mathbf{c}^r)$$
(7)

Fig. 2 shows the network architecture of NeRFReN. Detailed network configurations can be found in the supplementary material. Note that the reflection fraction value  $\alpha$  is predicted along with transmitted density in the transmitted branch as it is a property of the reflective surface, uncorrelated with the reflected component. Also, only the transmitted color is conditioned on viewing direction in our design. So the low-frequency view-dependent effects (e.g. highlights) are modeled by the transmitted field, and the stable virtual image (without view-dependent effects) is modeled by the reflected field. The above assumptions approximate most scenes reasonably well in our experiments due to their validity and greatly reduce network complexity, making the ill-posed decomposition problem much easier to learn.

### 3.3. Geometric Priors

Decomposing the scene into transmitted and reflected components is an under-constrained problem. There are infinite number of solutions and bad local minima that may produce visually pleasing rendering results on the training images but fail to separate apart the reflected radiance field from the transmitted radiance field. Humans identify the reflected virtual image correctly because we are aware of the real-world geometry. Inspired by this, we propose to utilize two geometric priors, namely depth smoothness prior and bidirectional depth consistency (BDC) prior, to guide the decomposition of the scene.

**Depth smoothness.** We exploit a general prior that the depth map of the *transmitted component* should be locally smooth. Specifically, we apply the following regularization term:

$$\mathcal{L}_{d} = \sum_{p} \sum_{q \in \mathcal{N}(p)} \omega(p, q) ||t^{*}(p) - t^{*}(q)||_{1},$$

$$\omega(p, q) = \exp(-\gamma ||\mathbf{C}(p) - \mathbf{C}(q)||_{1})$$
(8)

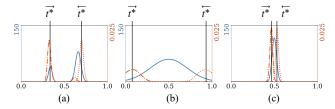


Figure 3. Illustrations for bidirectional depth consistency. Here we list three common density distributions (solid blue curve) along a ray in a neural radiance field. For each graph, the horizontal axis represents point locations along a ray. The dashdot and dotted orange curve are point weights (Eqs. (3) and (9)) at each location for calculating the forward and backward depth (Eqs. (5) and (9)) respectively. The computed depth values are marked with solid black lines. Only in case (c) we have a low BDC value, which corresponds to the expected shell-like geometry.

where  $t^*(p)$  is the approximated depth defined in Eq. (5), p denotes each pixel in a local patch,  $\mathcal{N}(p)$  is the set of its 8-connected neighbors,  $\mathbf{C}$  is the image color and  $\gamma$  is a hyperparameter.  $\omega(p,q)$  is a decay factor to re-weight (relax) the constraint based on the color gradient since depth discontinuities are often accompanied with abrupt color changes.

This prior is reasonable under our setting since most of the reflectors in the real world are planar surfaces, which show smooth depth changes in the reflected areas. Local depth smoothness priors are widely adopted in traditional stereo matching [19,20,31], but rarely explored in the training of neural representations. To apply this regularization during training, we sample patches instead of pixels.

**Bidirectional depth consistency.** The depth smoothness prior encourages correct geometry for the transmitted part. We now put constraints on the reflected part by assuming it has a simple geometry, where each ray only hits a single opaque surface. This assumption can help since we can only see the reflected objects from limited viewing angles so that they are, to some extend, similar to a textured *solid shell*. To describe this kind of simplicity in mathematical form, we propose a novel bidirectional depth consistency prior to encourage the aforementioned characteristic. We first define a new *backward depth*  $\overleftarrow{t}^*$  along ray  $\mathbf{r}$  as the expected termination point seeing the volume from the opposite direction of  $\mathbf{r}$ :

$$\overleftarrow{t}^*(\mathbf{r};\sigma) = \sum_{i} \overleftarrow{\omega}_i t_i = \sum_{i} \overleftarrow{T}_i(\sigma) (1 - \exp(-\sigma_i \delta_i)) t_i$$
(9)

where  $\overleftarrow{T}_i(\sigma) = \exp(-\sum_{j>i} \sigma_j \delta_j)$ . Denote  $\overrightarrow{t}^*$  as previous  $t^*$ , then our proposed bidirectional depth consistency (BDC) is defined as follows:

$$\mathcal{L}_{bdc} = \sum_{\mathbf{r}} ||\overrightarrow{t}^*(\mathbf{r}; \sigma^r) - \overleftarrow{t}^*(\mathbf{r}; \sigma^r)||_1 \qquad (10)$$

<sup>&</sup>lt;sup>1</sup>These assumptions may not hold if there exist reflectors in the reflected objects or due to severe Fresnel Effect.

This regularization poses a restriction on the density distribution along a ray, forcing it to be unimodal and have small variance. The idea is demonstrated in Fig. 3. Here we consider three representative types of density distribution along the ray in a neural radiance field. If the ray hits multiple surfaces as in (a) or marches in a "foggy" area without a clear surface as in (b), the forward and backward depth is not consistent as marked in the figure. The two depth values become close only if the density distribution is unimodal and has small variance as in (c). Intuitively, this requires the reflected component to have a "shell"-like geometry.

### 3.4. Warm-up Training

The overall loss used to optimize NeRFReN is the weighted combination of photometric loss and the proposed geometric priors:

$$\mathcal{L} = \mathcal{L}_{pm} + \lambda_d \mathcal{L}_d + \lambda_{bdc} \mathcal{L}_{bdc} \tag{11}$$

The magnitude of the geometric priors can greatly influence the decomposition results, which requires careful tuning of the weighting hyper-parameters which can hardly be shared across scenes. It is difficult to get a balance between the photometric loss and the geometric constraints especially at the early stage of training, due to the following reasons. If the geometric constraints dominate, the model will stuck into a bad local minima by using only one of the components to explain the whole scene while leaving the other empty. On the other hand, if the photometric loss dominates, insufficient geometric regularizations are provided, leading to suboptimal decomposition results.

Based on the above observations, we propose a universal training strategy, avoiding the need for tuning hyperparameters for each scene and effectively stabilize the training process. Specifically, we take inspirations from learning rate warm-up and propose to "warm-up" the geometric constraints. Denote the weighting parameters as  $\lambda_d$  and  $\lambda_{bdc}$ . We set  $\lambda_d$  and  $\lambda_{bdc}$  to be small at the beginning to get a reasonable initial state, and gradually increase the weights to relatively large values as the training proceeds. Large weights impose strong constraints on the geometry of the transmitted and reflected component, but will not lead to bad local minima due to the initialization phase. Then we gradually decrease the weights to concern more on photometric loss to get more accurate renderings. We refer to the supplementary material for more details about the warm-up training.

#### 3.5. Interactive Setting

The proposed geometric priors and training strategy work well when the transmitted geometry can be correctly estimated from the images. However, there exist more challenging cases, such as texture-less reflectors like mirrors, where the unsupervised decomposition usually fails.

Thanks to the additive formulation in Eqs. (1) and (7), we can utilize extra information such as manually labeled reflection fraction maps.

We exploit an interactive setting where the user provides binary masks of a small number of training images, with 1 and 0 denoting reflective and non-reflective regions respectively. L1 loss is used to encourage consistency between the predicted reflection fraction map  $\beta$  and the user-provided masks:

$$\mathcal{L}_{\beta} = \sum_{p} ||\widehat{\beta}(p) - \beta(p)||_{1}$$
 (12)

where  $\widehat{\beta}(p) = \beta(\mathbf{r}(p); \sigma^t, \alpha)$  is the estimation of the reflection fraction, and  $\beta(p)$  is the value of the user-provided binary mask at pixel p. With the help of this extra supervision, we are able to successfully isolate the reflected component in several challenging scenarios as demonstrated in Fig. 4. These scenarios are hard to deal with using existing novel view synthesis techniques.

# 4. Experiments

In this section, we first demonstrate how our method decomposes scenes with reflections into transmitted and reflected components, and composes them using the learned reflection fraction map to produce realistic view synthesis results (Sec. 4.1). Then, we compare with NeRF [13] and its naïve variant to show that NeRFReN achieves comparable visual quality as well as qualitatively better depth estimation results on several self-captured scenes (Sec. 4.2). We validate our design choices on the geometric priors and warm-up training strategy in Sec. 4.3, and finally provide applications for reflection removal and scene editing in Sec. 4.4.

**Baselines.** We compare NeRFReN with NeRF and a variant of NeRF which we call NeRF-D. NeRF-D applies our proposed depth smoothness constraint on the original NeRF, which is expected to model the reflected image solely by the surface point itself rather than all the point behind it along this viewing direction.

**Datasets.** Due to the lack of real-world datasets with strong reflections for the view synthesis task, we introduce RFFR (Real Forward-Facing with Reflections) dataset, containing 6 captured forward-facing scenes with strong reflection effects caused by glass and mirrors. We split the images into training and test set, and report the qualitative and quantitative results on test images.

**Training details.** To make fair comparisons, we design the networks to have roughly the same number of parameters with the original NeRF model. We simultaneously optimize a coarse and a fine network, and sample 64 points at both coarse and fine stage. All the models are trained for 40 epochs on each scene using Adam [8] optimizer with a learning rate of 5e-4. The maximum value for  $\mathcal{L}_d$  and  $\mathcal{L}_{bdc}$ 

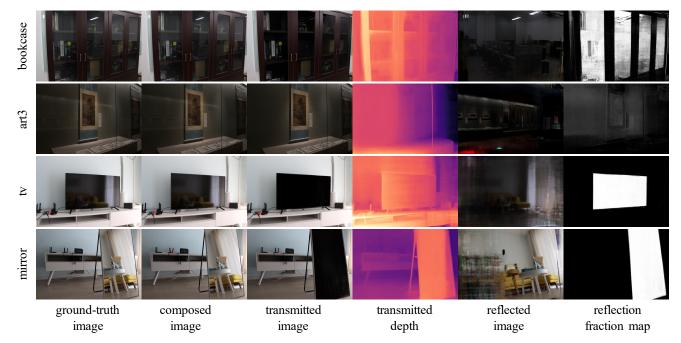


Figure 4. Decomposition results of NeRFReN on 4 of the RFFR scenes. The decomposed images and depth estimations are highly consistent with human perception.

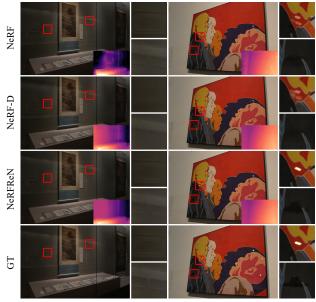


Figure 5. Visual comparisons between NeRF, NeRF-D and NeR-FReN. NeRFReN achieves comparable or better novel view synthesis quality with physically correct depth estimation. Zoom in for more details.

are 0.1 and 0.05. More details can be found in the supplementary material.

# 4.1. Decomposition

In Fig. 4 we show how NeRFReN decomposes the scene and performs view synthesis on four of the RFFR scenes.

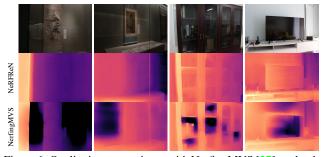


Figure 6. Qualitative comparisons with NerfingMVS [27] on depth estimation. NerfingMVS fails in such scenes with severe reflections, behaving similar to NeRF.

The transmitted image, reflected image, and reflection fraction map are rendered from the predicted transmitted and reflected neural radiance fields. The composed image is generated by combining the transmitted image and the reflected image weighted by the reflection fraction map according to Eq. (1). The depth values are computed by Eq. (5). For bookcase and painting, the decomposition is inferred from the training images alone. And for tv and mirror, 1 and 4 manually-annotated reflection masks are utilized respectively as extra information, as described in Sec. 3.5.

We can see from Fig. 4 that NeRFReN can perform transmission-reflection decomposition that is consistent with human perception while producing high-quality view synthesis results. The learned reflection fraction map roughly indicates the surface material, with large values for reflectors and small values for non-reflectors. Note that we only intend to model the stable virtual image by the

	PSNR↑					
Method	art1	art2	art3	bookcase	tv	mirror
NeRF	36.48	42.63	41.18	29.50	33.47	32.22
NeRF-D	36.49	41.58	39.80	<u>29.78</u>	33.02	32.33
NeRFReN	39.49	<u>42.33</u>	<u>41.03</u>	30.18	33.24	33.30
	SSIM↑					
Method	art1	art2	art3	bookcase	tv	mirror
NeRF	0.975	0.974	0.973	0.883	0.960	0.944
NeRF-D	0.971	0.968	0.965	0.876	0.954	0.939
NeRFReN	0.978	0.972	0.970	0.890	0.955	0.947
	LPIPS↓					
Method	art1	art2	art3	bookcase	tv	mirror
NeRF	0.029	0.059	0.053	0.078	0.054	0.066
NeRF-D	0.027	0.070	0.117	0.136	0.063	0.072
NeRFReN	0.029	<u>0.067</u>	<u>0.072</u>	<u>0.100</u>	<u>0.061</u>	0.071

Table 1. View synthesis results of NeRF, NeRF-D and NeRFReN on RFFR scenes in PSNR, SSIM [26] and LPIPS [32]. NeRFReN performs comparable with NeRF and better than NeRF-D.

reflected field, and leave the low-frequency highlights to the view-dependency in the transmitted field. For example, there are highlights on the frames of the bookcase, where the reflection fraction is almost zero.

### 4.2. Comparisons

We compare NeRFReN with NeRF and NeRF+D on our RFFR test set using three metrics: PSNR, SSIM [26] and LPIPS [32] (see Tab. 1). We also provide qualitative comparisons in Fig. 5. We urge the readers to refer to the supplementary videos for a more intuitive visual comparison.

Quantitatively, NeRFReN significantly outperforms NeRF on art1 and mirror in PSNR, and performs comparably with NeRF on rest of the scenes. But as demonstrated in Sec. 3.1, NeRF produces inaccurate depth estimation due to the mixed geometry of the transmitted and reflected components, as shown on the bottom left corner of the NeRF rendering results in Fig. 5. NeRFReN models the scene with separate neural radiance fields, and provides physically correct depth map by taking the depth estimation of the transmitted field. Also, NeRF generates suboptimal renderings when the multi-view consistency is violated while NeRFReN does not suffer from such restrictions, as shown in the *mirror* case in Fig. 1(b). NeRF-D produces more correct depth estimation than NeRF by adopting the depth smoothness regularization, and condition the surface color on viewing direction. However, it synthesizes blurry results due to the insufficient representation power of NeRF's view-dependency in modeling complex reflections. The quantitative results conform with this claim that NeRF-D consistently underperforms NeRF and NeRFReN.

To demonstrate the depth estimation quality of NeR-FReN, we also qualitatively compare with Nerfing-MVS [27] on RFFR scenes. Results are shown in Fig. 6. NerfingMVS utilizes monocular depth estimation priors

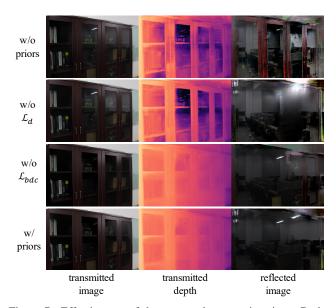


Figure 7. Effectiveness of the proposed geometric priors. Both priors are essential to get physically sound decompositions.

and post-filtering to achieve promising results on Scan-Net scenes, but struggles on scenes with complex reflections. This is because NerfingMVS initializes the depth maps based on Multi-View-Stereo output, which cannot give faithful depth estimates in such cases.

To conclude, NeRFReN achieves visually pleasing view synthesis results and physically correct depth estimation results at the same time. The formulation of NeRFReN naturally relax the multi-view consistency of NeRF by combining the transmitted and reflected part in the image domain, which greatly facilitate novel view synthesis in challenging scenes like those with mirrors.

#### 4.3. Ablation Studies

We discuss the necessity of several key design choices, and demonstrate their importance to getting faithful decompositions and correct view synthesis results.

Geometric Priors We train NeRFReN without any geometric priors and with only one of the priors, to see the impact of these priors on the decomposition quality. The results are shown in Fig. 7. Without any priors (first row), we find the optimization process to be highly under-controlled, largely depending on the network initialization. In this case, the decomposition results are not reasonable since the transmitted and reflected part are mixed together. Without the depth smoothness prior (second row), there is not enough constraint on the transmitted geometry, letting it contain reflected objects and producing wrong depth. Without the bidirectional depth consistency (third row), there will be redundant contents left in the reflected component (the bookcase frame). We make the conclusion that both priors are essential to get reasonable solutions for this under-constrained

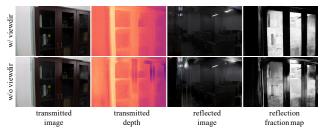


Figure 8. The effectiveness of conditioning the transmitted radiance on viewing direction. Without this view-dependency, low-frequency reflections like highlights are modeled with foggy contents in the reflected component, leading to inaccurate depth estimation.



Figure 9. Examples of replacing the reflected image (with the *room* scene in [13]). This may be used to synthesize self-reflections of the user for higher realism.

problem (fourth row).

**View-dependency** NeRFReN conditions the color of the transmitted component on viewing direction to model low-frequency view-dependent effects. We remove this dependency on the *bookcase* scene and show the results in Fig. 8. Without the view-dependency, highlights on the bookcase frame are modeled with the combined effect of the reflected image and the reflection fraction map. This results in inaccurate depth estimation (dark regions on the predicted depth map), and redundancies in the reflected component which do not belong to the virtual geometry.

Warm-up Training We exploit two alternative training strategies to demonstrate the effectiveness of warm-up training: (1) training with strong geometric constraints ( $\mathcal{L}_d = 0.1, \mathcal{L}_{bdc} = 0.05$ ) directly without warm-up; (2) incorporating view-dependency directly from the beginning of training. For the first setting, the transmitted depth can be overly smoothed, and the reflected component quickly converges to empty due to the strong constraints without proper initialization. For the second setting, there may be some low-frequency component of the reflected part "leaked" into the transmitted part and modeled with view-dependency, which is not expected. We refer to the supplementary material for visualized results.

#### 4.4. Applications

Enabling user editing for neural scene representations has been attracting attention in the community [2, 6, 9, 24, 30, 33]. Existing techniques either achieve material edit-

ing or relighting by reflectance decomposition [2,24,33] or model the scene at object-level to directly manipulate the neural radiance fields [6,9,30]. Benefit from the formulation in Eq. (1), NeRFReN enables scene editing in the image domain while maintaining view consistency, which is more intuitive and makes it possible to work with other scene representations.

**Reflection removal.** Our formulation naturally supports the application for reflection removal by taking only the transmitted image. See column 3 of Fig. 4.

**Reflection substitution.** We achieve reflection substitution by replacing the reflection image  $I_r$  by images coming from other neural radiance fields, or even from other scene representations like mesh. Fig. 9 shows two examples of replacing the reflections with images rendered from another NeRF model trained on the *room* scene [13]. This could be further promoted to synthesize self-reflections of the user to provide even more immersive experiences. We hope the image-based formulation of NeRFReN can inspire future research about combining multiple scene representations.

#### 5. Limitations

One major limitation of our method is that we only support almost planar reflectors. Curved reflective surfaces that do not produce stable virtual images cannot be modeled by our image-based formulation. We support multiple reflective surfaces as long as the geometries of the virtual images do not coincide, but may produce inaccurate results otherwise. Also, we do not consider the view-dependent effects of the reflected objects, and ignore the view-dependency of the reflection fraction values caused by Fresnel effect. Experimental results on some of the aforementioned cases can be found in the supplements.

## 6. Conclusion

We propose NeRFReN to enhance NeRF in scenes with reflections. We decompose the scene into transmitted and reflected components, model them with separate neural radiance fields, and synthesize novel views by weighted combination of the renderings from the two fields. We exploit geometric priors and special training strategy to encourage proper decomposition. What's more, user-provided reflection masks can be utilized to aid the decomposition in challenging cases like mirrors. Our method achieves comparable view synthesis quality with NeRF but is more explainable since the faithful decomposition results are consistent with human perception. Finally, potential applications enabled by NeRFReN, including depth estimation, reflection removal and reflection substitution are investigated to encourage further research about scene understanding and neural editing.

#### References

- [1] Kara-Ali Aliev, Artem Sevastopolsky, Maria Kolos, Dmitry Ulyanov, and Victor Lempitsky. Neural point-based graphics. In Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part XXII 16, pages 696–712. Springer, 2020. 2
- [2] Mark Boss, Raphael Braun, Varun Jampani, Jonathan T Barron, Ce Liu, and Hendrik Lensch. Nerd: Neural reflectance decomposition from image collections. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 12684–12694, 2021. 8
- [3] Chris Buehler, Michael Bosse, Leonard McMillan, Steven Gortler, and Michael Cohen. Unstructured lumigraph rendering. In *Proceedings of the 28th annual conference on Computer graphics and interactive techniques*, pages 425– 432, 2001. 2
- [4] Zhiqin Chen and Hao Zhang. Learning implicit fields for generative shape modeling. In *Proceedings of the IEEE/CVF* Conference on Computer Vision and Pattern Recognition, pages 5939–5948, 2019. 2
- [5] John Flynn, Michael Broxton, Paul Debevec, Matthew Du-Vall, Graham Fyffe, Ryan Overbeck, Noah Snavely, and Richard Tucker. Deepview: View synthesis with learned gradient descent. In *Proceedings of the IEEE/CVF Conference* on Computer Vision and Pattern Recognition, pages 2367– 2376, 2019. 2
- [6] Michelle Guo, Alireza Fathi, Jiajun Wu, and Thomas Funkhouser. Object-centric neural scene rendering. arXiv preprint arXiv:2012.08503, 2020. 8
- [7] Peter Hedman, Tobias Ritschel, George Drettakis, and Gabriel Brostow. Scalable inside-out image-based rendering. *ACM Transactions on Graphics (TOG)*, 35(6):1–11, 2016. 2
- [8] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980, 2014. 5
- [9] Steven Liu, Xiuming Zhang, Zhoutong Zhang, Richard Zhang, Jun-Yan Zhu, and Bryan Russell. Editing conditional radiance fields. arXiv preprint arXiv:2105.06466, 2021. 8
- [10] Stephen Lombardi, Tomas Simon, Jason Saragih, Gabriel Schwartz, Andreas Lehrmann, and Yaser Sheikh. Neural volumes: Learning dynamic renderable volumes from images. arXiv preprint arXiv:1906.07751, 2019. 2
- [11] Nelson Max. Optical models for direct volume rendering. *IEEE Transactions on Visualization and Computer Graphics*, 1(2):99–108, 1995. 3
- [12] Lars Mescheder, Michael Oechsle, Michael Niemeyer, Se-bastian Nowozin, and Andreas Geiger. Occupancy networks: Learning 3d reconstruction in function space. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 4460–4470, 2019. 2
- [13] Ben Mildenhall, Pratul P Srinivasan, Matthew Tancik, Jonathan T Barron, Ravi Ramamoorthi, and Ren Ng. Nerf: Representing scenes as neural radiance fields for view synthesis. In *European conference on computer vision*, pages 405–421. Springer, 2020. 1, 2, 3, 5, 8
- [14] Jeong Joon Park, Peter Florence, Julian Straub, Richard Newcombe, and Steven Lovegrove. Deepsdf: Learning con-

- tinuous signed distance functions for shape representation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 165–174, 2019. 2
- [15] Gernot Riegler and Vladlen Koltun. Free view synthesis. In European Conference on Computer Vision, pages 623–640. Springer, 2020. 2
- [16] Gernot Riegler and Vladlen Koltun. Stable view synthesis. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 12216–12225, 2021.
- [17] Johannes Lutz Schönberger and Jan-Michael Frahm. Structure-from-motion revisited. In Conference on Computer Vision and Pattern Recognition (CVPR), 2016.
- [18] Johannes Lutz Schönberger, Enliang Zheng, Marc Pollefeys, and Jan-Michael Frahm. Pixelwise view selection for unstructured multi-view stereo. In European Conference on Computer Vision (ECCV), 2016. 2
- [19] Sudipta N Sinha, Johannes Kopf, Michael Goesele, Daniel Scharstein, and Richard Szeliski. Image-based rendering for scenes with reflections. ACM Transactions on Graphics (TOG), 31(4):1–10, 2012. 2, 3, 4
- [20] Sudipta N Sinha, Drew Steedly, and Richard Szeliski. Piecewise planar stereo for image-based rendering. In 2009 IEEE 12th International Conference on Computer Vision, pages 1881–1888. IEEE. 4
- [21] Vincent Sitzmann, Justus Thies, Felix Heide, Matthias Nießner, Gordon Wetzstein, and Michael Zollhofer. Deepvoxels: Learning persistent 3d feature embeddings. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 2437–2446, 2019. 2
- [22] Vincent Sitzmann, Michael Zollhöfer, and Gordon Wetzstein. Scene representation networks: Continuous 3d-structure-aware neural scene representations. *arXiv preprint arXiv:1906.01618*, 2019. 2
- [23] Noah Snavely, Steven M Seitz, and Richard Szeliski. Photo tourism: exploring photo collections in 3d. In ACM siggraph 2006 papers, pages 835–846. 2006.
- [24] Pratul P Srinivasan, Boyang Deng, Xiuming Zhang, Matthew Tancik, Ben Mildenhall, and Jonathan T Barron. Nerv: Neural reflectance and visibility fields for relighting and view synthesis. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 7495–7504, 2021. 8
- [25] Justus Thies, Michael Zollhöfer, and Matthias Nießner. Deferred neural rendering: Image synthesis using neural textures. ACM Transactions on Graphics (TOG), 38(4):1–12, 2019.
- [26] Zhou Wang, Eero P Simoncelli, and Alan C Bovik. Multiscale structural similarity for image quality assessment. In The Thrity-Seventh Asilomar Conference on Signals, Systems & Computers, 2003, volume 2, pages 1398–1402. Ieee, 2003. 7
- [27] Yi Wei, Shaohui Liu, Yongming Rao, Wang Zhao, Jiwen Lu, and Jie Zhou. Nerfingmvs: Guided optimization of neural radiance fields for indoor multi-view stereo. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 5610–5619, 2021. 6, 7

- [28] Suttisak Wizadwongsa, Pakkapon Phongthawee, Jiraphon Yenphraphai, and Supasorn Suwajanakorn. Nex: Real-time view synthesis with neural basis expansion. In *Proceedings* of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 8534–8543, 2021. 2
- [29] Jiamin Xu, Xiuchao Wu, Zihan Zhu, Qixing Huang, Yin Yang, Hujun Bao, and Weiwei Xu. Scalable image-based indoor scene rendering with reflections. ACM Transactions on Graphics (TOG), 40(4):1–14, 2021.
- [30] Bangbang Yang, Yinda Zhang, Yinghao Xu, Yijin Li, Han Zhou, Hujun Bao, Guofeng Zhang, and Zhaopeng Cui. Learning object-compositional neural radiance field for editable scene rendering. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 13779–13788, 2021. 8
- [31] Chi Zhang, Zhiwei Li, Rui Cai, Hongyang Chao, and Yong Rui. As-rigid-as-possible stereo under second order smoothness priors. In *European Conference on Computer Vision*, pages 112–126. Springer, 2014. 4
- [32] Richard Zhang, Phillip Isola, Alexei A Efros, Eli Shechtman, and Oliver Wang. The unreasonable effectiveness of deep features as a perceptual metric. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 586–595, 2018. 7
- [33] Xiuming Zhang, Pratul P Srinivasan, Boyang Deng, Paul Debevec, William T Freeman, and Jonathan T Barron. Nerfactor: Neural factorization of shape and reflectance under an unknown illumination. *arXiv* preprint arXiv:2106.01970, 2021. 3, 8