NeuralRoom: Geometry-Constrained Neural Implicit Surfaces for Indoor Scene Reconstruction

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We present a novel neural surface reconstruction method called NeuralRoom for reconstructing room-sized indoor scenes directly from a set of 2D images. Recently, implicit neural representations have become a promising way to reconstruct surfaces from multiview images due to their high-quality results and simplicity. However, implicit neural representations usually cannot reconstruct indoor scenes well because they suffer severe shape-radiance ambiguity. We assume that the indoor scene consists of texture-rich and flat texture-less regions. In texture-rich regions, the multiview stereo can obtain accurate results. In the flat area, normal estimation networks usually obtain a good normal estimation. Based on the above observations, we reduce the possible spatial variation range of implicit neural surfaces by reliable geometric priors to alleviate shape-radiance ambiguity. Specifically, we use multiview stereo results to limit the NeuralRoom optimization space and then use reliable geometric priors to guide NeuralRoom training. Then the NeuralRoom would produce a neural scene representation that can render an image consistent with the input training images. In addition, we propose a smoothing method called perturbation-residual restrictions to improve the accuracy and completeness of the flat region, which assumes that the sampling points in a local surface should have the same normal and similar distance to the observation center. Experiments on the ScanNet dataset show that our method can reconstruct the texture-less area of indoor scenes while maintaining the accuracy of detail. We also apply NeuralRoom to more advanced multiview reconstruction algorithms and significantly improve their reconstruction quality.

Fig. 1. We present a system called NeuralRoom for reconstructing a room-sized indoor scene from 2D images. There are many texture-less regions in indoor scenes, making conventional multiview stereo methods fail in reconstruction. The implicit neural representation method has recently become a promising reconstruction method due to its simplicity and high reconstruction quality. However, shape-radiance ambiguity makes it unable to reconstruct indoor scenes well. NeuralRoom effectively integrates normal and depth information to overcome ambiguity, which guarantees reconstruction details and completeness.

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1 INTRODUCTION
Reconstructing 3D geometries from multiview images is a fundamental topic in computer vision and graphics. The reconstructed model can be applied to VR/AR, video games, 3D printing and CAD manufacturing. Reconstruction of outdoor scenes and single objects with rich textures has been widely studied. However, few studies on indoor multiview reconstruction are directly based on color images. Objects in indoor scenes are usually of a single color, such as walls, furniture, and floors, which cannot be well restricted by photometric consistency.

MVS reconstruction algorithms have difficulty performing feature matching on texture-less areas, which leads to incompleteness and a large number of outliers.

Learning-based per-view depth estimation methods can obtain a good depth estimation for a single image. However, although it has good performance in quantitative evaluation, the fused 3D model is usually inaccurate due to the lack of consistency constraints between views. In addition, the areas with sudden depth changes are usually oversmoothed.

Another kind of learning-based reconstruction method directly extracts a 3D mesh from a volumetric representation. [Murez et al. 2020; Sun et al. 2021a] obtained effective reconstruction of indoor scenes. The reconstruction results of these methods generally have better completeness, but the scene details need to be further improved.

Recently, neural surface reconstruction methods have significantly promoted the development of 3D reconstruction, which achieves better reconstruction quality than conventional reconstruction approaches. In addition, these methods have the potential to reconstruct objects with non-Lambertian, less observed regions and complex geometry.

NeRF-based methods [Mildenhall et al. 2020] learn a function that maps 3D coordinates and 2D viewing directions to opacity and color values. However, since additional viewing directions need to be an additional input, the solution is not unique to explaining the input training images when lacking explicit or implicit regularization. Such a situation is called shape-radiance ambiguity [Buehler et al. 2001; Chai et al. 2000;Debevec et al. 1996; Zhang et al. 2020a], which means incorrect geometry can render an image consistent with the input training image. Shape-radiance ambiguity becomes the bottleneck in the reconstruction of indoor scenes for rendering-based surface reconstruction methods (Figure 2), although these methods [Oechsle et al. 2021; Wang et al. 2021b; Yariv et al. 2021] yield impressive reconstruction results on a single object.

In this work, we propose a novel neural surface reconstruction method called NeuralRoom to assign appropriate global and local constraints between sampling rays to overcome shape-radiance ambiguity. We assume that the indoor scene is composed of two parts. The first part contains rich textured areas and edges such as object edges and various color decorations. The other part contains texture-less regions, such as walls and ground. We found that MVS can obtain high-precision estimates in textured areas but obtain relatively inaccurate results in texture-less areas. In contrast, neural network-based normal estimation methods [Bae et al. 2021; Do et al. 2020; Huang et al. 2019; Wang et al. 2020] always obtain a good estimation on flat areas but obtain inaccurate results on edges and rich textured areas (Figure 3). In our method, we combine their advances and propose a new smoothing term to alleviate shape-radiance ambiguity.

Specifically, our system consists of two main stages. The first stage is geometry prior acquisition (Figure 5). We use multiview stereo to calculate the depth map and bounding box based on the depth fusion result. Then, we generate the distance prior from the depth map of each view. In addition, we use a learning-based normal estimation network to predict the normal map and filter it with uncertainty. The distance prior and normal prior are used to guide the next stage NeuralRoom differentiable renderer.

The NeuralRoom renderer takes the above priors to optimize the implicit neural surface. The distance prior ensures the accuracy of reconstructed details and the normal prior limits the geometry feature of the texture-less region. To further improve the reconstruction quality of the flat regions, we conduct a smoothing method called perturbation-residual restriction for our NeuralRoom renderer. We assume that the sampling points on the local surface should be close to each other. If the local area is flat, the normal of sampling points should be the same.

Our main contributions are the following:

- Introduce several efficient geometric priors for overcoming shape-radiance ambiguity. The distance prior acquired by MVS helps improve the detail accuracy. The normal prior helps enhance the completeness and accuracy of the texture-less region.
- Develop perturbation-residual restrictions working as smoothing terms to improve the accuracy and completeness of the flat and texture-less regions. There are some noise data in the priors, so this smoothing term can further enhance the reconstruction quality.

Experimental results on the ScanNet dataset show that we have successfully applied multiview neural surface reconstruction for indoor scene reconstruction. Our complete framework has significantly improved state-of-the-art multiview reconstruction results on the tested indoor scenes. In addition, we use mobile phones to take photos of real-world scenes and successfully use our proposed system for reconstruction.

2 RELATED WORK

2.1 Multiview Reconstruction

Multiview reconstruction aims to reconstruct the three-dimensional geometric model of the scene from a set of images with or without calibrated camera poses. The key point of the image-based approach is photometric consistency assumptions. Among all kinds of methods, depth-map merging-based methods are the most widely used.
Multiview stereo has been widely studied [Seitz et al. 2006]. Traditional MVS methods [Galliani et al. 2015; Schonberger and Frahm 2016; Xu and Tao 2019] estimate the corresponding depth map for each input high-resolution image offline and then fuse it into the final three-dimensional model [Bernardini et al. 1999; Kazhdan et al. 2006; Merrell et al. 2007]. These MVS methods often use the idea of sampling and propagation in PatchMatch to make depth estimation more effective. The learning based MVS approaches [Chen et al. 2019; Cheng et al. 2020; Ding et al. 2021; Gu et al. 2020; Kuhn et al. 2020; Wang et al. 2021a; Wei et al. 2021b; Xu et al. 2021; Yan et al. 2020; Yang et al. 2020; Yao et al. 2018, 2019; Zhang et al. 2020b] have become popular in recent years and have shown some advantages in terms of accuracy and completeness in specific datasets. Most of the deep learning methods take MVSNet [Yao et al. 2018] as their skeleton and are based on plane-sweep stereo [Collins 1996]. They use a convolutional neural network to extract higher dimensional 2D features in the image, usually following a 3D convolution to regress the depth for per pixel. The 3D CNN is time- and memory-consuming due to the large number of parameters. The following works adopt a pyramid structure [Cheng et al. 2020; Gu et al. 2020; Liao et al. 2021; Yang et al. 2020] or recurrent network [Wei et al. 2021b; Yan et al. 2020; Yao et al. 2019] to reduce the memory consumption. Some other work integrates PatchMatch [Wang et al. 2021a], uncertainty [Zhang et al. 2020b], attention mechanism [Ding et al. 2021], semantic segmentation [Xu et al. 2021] and other mechanisms [Chen et al. 2019; Kuhn et al. 2020] into MVS approaches.

For indoor scenes, because there are a large number of weak texture areas in the scene, such as walls, floors and solid color furniture, the correspondence matching quality of MVS is usually poor, which leads to missing parts and outliers in the reconstruction. Previous works have attempted to reconstruct texture-less regions with different methods, such as multiresolution [Xu and Tao 2019], planar priors [Sun et al. 2021b; Xu and Tao 2020a], and depth map completion [Kuhn et al. 2020; Liu et al. 2020b]. These methods can improve the reconstruction results of the texture-less region to a certain extent and are better than the conventional methods in quantitative evaluation. However, they still cannot obtain a satisfactory result in the indoor scene.

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Fig. 2. Inherent shape-radiance ambiguity. For each set of results, the first row shows the reconstruction results. The second row shows rendering results from the implicit neural representation. State-of-the-art methods [Oechsle et al. 2021; Wang et al. 2021b; Yariv et al. 2021] can yield impressive high-quality reconstruction of a single object, while they often yield unsatisfactory reconstruction and rendering results for indoor scenes. Optimization of implicit neural representations easily falls into a local optimum, which will result in an incorrect reconstruction or even fail in reconstruction.
Some learning-based multiview depth estimation and SLAM methods [Hou et al. 2019; Jiang et al. 2021; Long et al. 2021a,b; Rich et al. 2021; Teed and Deng 2018; Wang and Shen 2018] use data-driven methods to reduce the over-reliance on the photometric consistency assumption. They can quickly produce a low-resolution dense depth map. These methods can assign depth values to texture-less areas, but the areas with sudden depth changes are often oversmoothed. The 3D model acquired by TSDF fusion can show the general appearance of the scene, while the accuracy is poor. In addition, after obtaining the raw reconstruction through MVS, object or scene completion algorithms [Bokhovkin and Dai 2022; Dai et al. 2020, 2021; Zhang et al. 2022] can be used to complete and optimize the scene.

2.2 Implicit Neural Representation

Implicit neural representations represent scenes as a continuous implicit function, which can represent high-resolution geometries in finite memory. This implicit representation has been successfully used in novel view synthesis [Barron et al. 2021; Liu et al. 2020a; Mildenhall et al. 2020; Müller et al. 2022; Niemeyer et al. 2021; Roessle et al. 2021; Tancik et al. 2022; Xiangli et al. 2021; Xu et al. 2022a; Yu et al. 2021], shape representation [Atzmon et al. 2019; Atzmon and Lipman 2020; Genova et al. 2019; Mescheder et al. 2019; Michalkiewicz et al. 2019; Müller et al. 2022; Park et al. 2019; Peng et al. 2020], human reconstruction [Saito et al. 2019, 2020], relighting [Philip et al. 2021], and multiview 3D reconstruction [Niemeyer et al. 2020; Oechsle et al. 2021; Wang et al. 2021b; Xu et al. 2022b; Yariv et al. 2020].

[Choy et al. 2016; Ji et al. 2017, 2020; Kar et al. 2017; Murez et al. 2020; Sun et al. 2021a] presented end-to-end 3D reconstruction methods that use a global volumetric representation to assemble features from all views and then predict the 3D model directly from the feature volume. [Liu et al. 2020a; Murez et al. 2020] presented learning-based dense reconstruction methods for indoor scenes that can obtain better reconstruction than the previous methods in terms of quality and quantitative comparison. However, the details of the reconstruction results need to be improved.

Recently, differentiable rendering multiview 3D reconstruction methods have significantly advanced the development of 3D reconstruction and achieve better reconstruction quality than other conventional reconstruction methods on a single object. There are two types of rendering methods: surface rendering methods [Kellnhofer et al. 2021; Niemeyer et al. 2020; Yariv et al. 2020] and volume rendering methods [Mildenhall et al. 2020; Müller et al. 2022; Oechsle et al. 2021; Wang et al. 2021b; Yu et al. 2021]. Surface rendering-based methods assume that the radiance of a ray required for rendering is only related to the intersection of the ray and the geometric surface. This makes the gradient only backpropagated to the local area at the intersection. These methods usually cannot deal with complex geometries well and rely heavily on the object’s mask. When the mask is missing, reconstruction usually fails. Volume rendering-based methods assume that the rendering color is related to the radiance and the corresponding alpha weight at all spatial locations through which the ray passes. Therefore, the gradient can be backpropagated to all sites involved in rendering. These methods can reconstruct complex scenes without a mask and deal with some scenes with sudden depth changes. However, it is usually unable to obtain high-precision geometric surfaces, especially for the texture-less region, due to the lack of geometric surface constraints. In addition, the reconstruction may contain conspicuous noises.

The rendering-based implicit neural representation shows the potential to replace traditional MVS reconstruction. However, its performance is not as good as that of traditional reconstruction methods in indoor scenes. NeRF-based methods [Mildenhall et al. 2020] map a 5D input (3D coordinates plus the 2D viewing direction) to opacity and color values, which easily suffers from inherent shape-radiance ambiguity due to the additional input dimensions and the lack of implicit or explicit regularization in the implicit representation.

Many works use the depth value as a constraint to alleviate this ambiguity [Chen et al. 2021; Roessle et al. 2021; Wei et al. 2021a; Xu et al. 2022a] in their respective fields. [Roessle et al. 2021; Wei et al. 2021a] used the monocular depth estimation network optimized by MVS results to provide a distance prior for each pixel to reduce shape-radiance ambiguity and improve the effect of indoor depth estimation and novel view synthesis. However, the consistency between views of depth estimation is far from sufficient to obtain a satisfactory 3D model.

The concurrent works [Guo et al. 2022; Wang et al. 2022; Yu et al. 2022] have ideas similar to those of our work. These methods use depth estimation to provide depth cues and use normal information as additional constraints to reconstruct indoor scenes.

3 OVERVIEW

Shape-radiance ambiguity [Buehler et al. 2001; Chai et al. 2000; Debevec et al. 1996; Zhang et al. 2020a] often exists in the NeRF-based rendering method [Mildenhall et al. 2020]. A well-trained
NeuralRoom: Geometry-Constrained Neural Implicit Surfaces for Indoor Scene Reconstruction

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The goal of our system is to reconstruct indoor scenes directly from RGB images with known camera parameters. The system consists of two parts. First, we use the multiview stereo method [Schonberger and Frahm 2016] and the normal estimate network [Bae et al. 2021] to acquire the geometry prior. The distance prior acquired from MVS ensures the accuracy of texture-rich and edge areas, while the normal prior ensures the completeness of the texture-less region. Then, we use these geometry prior and RGB images to guide the optimization of the NeuralRoom module, which is a volume rendering-based neural surface reconstruction method. In addition, in the NeuralRoom module, we propose perturbation-residual restriction to constrain the implicit surface. Finally, we use ray tracing on the reconstructed scene and perform TSDF fusion to obtain the final 3D mesh model.

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Fig. 4. Method overview. The goal of our system is to reconstruct indoor scenes directly from RGB images with known camera parameters. The system consists of two parts. First, we use the multiview stereo method [Schonberger and Frahm 2016] and the normal estimate network [Bae et al. 2021] to acquire the geometry prior. The distance prior acquired from MVS ensures the accuracy of texture-rich and edge areas, while the normal prior ensures the completeness of the texture-less region. Then, we use these geometry prior and RGB images to guide the optimization of the NeuralRoom module, which is a volume rendering-based neural surface reconstruction method. In addition, in the NeuralRoom module, we propose perturbation-residual restriction to constrain the implicit surface. Finally, we use ray tracing on the reconstructed scene and perform TSDF fusion to obtain the final 3D mesh model.

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Fig. 5. Distance and normal priors. (a) Input RGB image. (b) Depth map estimated by COLMAP [Schonberger and Frahm 2016]. (c) Ground truth depth map in the ScanNet [Dai et al. 2017] dataset. (d) Uncertainty acquired by [Bae et al. 2021] indicating the corresponding normal estimation quality. The normal estimation result in the bright colored areas is inaccurate. (e) Normal map estimated by [Do et al. 2020]. (f) Ground truth normal map acquired by performing ray tracing on the ground truth mesh model.

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The method proceeds in three parts:

- Inside-out shooting which makes some areas only visible from almost the same direction.
- Large optimization space.

We introduce a novel multiview neural surface reconstruction method called NeuralRoom, which aims to handle the shape-radiance ambiguity in indoor scenes. Given a relatively accurate camera pose and varied observation directions, we use appropriate geometry cues to guide the optimization of neural representations and avoid falling into a local optimum. Specifically, we divide the scene into the textured and texture-less regions according to geometric features. For the textured and edge areas, we use the distance prior acquired by COLMAP [Schonberger and Frahm 2016], which is usually accurate. We give a high weight to make the implicit surface consistent with the distance prior. For flat and texture-less regions, we use the normal prior acquired by [Bae et al. 2021] to limit the local surface geometry. In addition, we propose smoothing terms called perturbation-residual restrictions to further improve the accuracy and completeness.

The method proceeds in three parts:

- Geometry prior acquisition. Section 4.1 introduces data preparation and how to acquire the distance and normal prior.
- NeuralRoom renderer. Section 4.2 and Section 4.3 introduce the NeuralRoom renderer and the perturbation-residual restrictions.
- Mesh extraction. Section 4.4 introduces our mesh extraction method.

4 METHOD

4.1 Preprocessing

**Image Processing.** First, we extract the images from the indoor video sequence. Usually, we would obtain thousands of photos.
Because imaging quality will affect the accuracy of MVS, normal estimation, and rendering-based reconstruction, we use a Laplacian filter for blurring detection to determine which images should be used in the experiment. Given a set of images, we divided every ten images into a subgroup. Then we calculate the Laplacian of the source image as a blurring degree. Each subset leaves only one optimal image with the largest Laplacian in the subgroup. All optimal images generate the image set \(I\) we used in the experiment.

**Distance Prior.** In the textured areas and edges, MVS can obtain high accuracy results. We hope to ensure the accuracy of these areas in NeuralRoom. We run COLMAP [Schonberger and Frahm 2016], a traditional multiview stereo method, on each selected image \(i\) with fixed camera intrinsic parameters \(K_i\) and extrinsic parameters \(T_i = [R_i|t_i]\) to acquire a per-view depth map \(D_i^{MVS}\). The depth map \(D_i^{MVS}\) has been filtered by geometric consistency and eroded by 3 pixels. We set the values to zero for pixels where the depth is not defined. Therefore, the acquired depth map \(D_i^{MVS}\) is sparser but more accurate.

We convert the depth to the distance between the camera center and the corresponding point for more convenient use in the optimization. We reproject the 2D coordinate to a 3D point in the world coordinate using \(D_i^{MVS}\) and corresponding parameters \(K_i\) and \(T_i\):

\[
X_i(p) = T_i^{-1}K_i^{-1}D_i^{MVS}(p) \tilde{p}, \quad \text{where } D_i^{MVS}(p) \neq 0,
\]

where \(p\) is the 2D pixel coordinate in \(i\), \(\tilde{p}\) is the homogeneous augmentation of \(p\), \(X_i\) is corresponding 3D point.

Each scene has a different size and location in world coordinates. Therefore, we normalize the scene into a cube with the center at the origin and a side length of 2. First, we fuse all depth maps into a point cloud and compute an axis-aligned bounding box. Then, we select the maximum bounding point \(X_{bbox}^{max}\) and the minimum bounding point \(X_{bbox}^{min}\). We can define the center of the scene in the real world as the translation \(t_{opt}\) to the optimization coordinate. We then further define the scale \(s\) which compresses the longest side length of the bounding box by \(s\) times, so we ensure that the reconstructed scene falls into the NeuralRoom optimization space. Finally, we define the distance prior \(D_i\) as

\[
D_i(p) = \|K_i^{-1}D_i^{MVS}(p) \tilde{p}\|/s, \quad \text{where } D_i^{MVS}(p) \neq 0.
\]

**Normal Prior and Uncertainty Acquisition.** Texture-less regions cannot be effectively constrained by photometric consistency loss, which always suffers from shape-radiance ambiguity. Therefore, we use the surface normal acquired from the neural network to guide the optimization of NeuralRoom. We take UncertSurfaceNormal [Bae et al. 2021] as our normal estimation module. [Bae et al. 2021] is a learning-based normal estimation method. It takes a single image as input, and the output contains an estimated normal map and corresponding uncertainty map. We assume that the position with large uncertainty is where the surface geometry changes sharply. The area with a smooth surface generally has less uncertainty.

The learning-based approaches always take a normal map calculated by a depth map as ground truth which is captured by a depth sensor. However, there is usually noise in the depth map obtained by the depth sensor. The depth varies greatly on edges, and the depth of special material surfaces is typically unable to be collected. In addition, the depth map acquired by the depth sensor needs to be converted to the image sensor coordinate system through extrinsic parameters. This transform also causes the depth value to be missing at the boundary. Therefore, the estimation of edges is usually inaccurate. We need an indication to determine which parts of the normal estimation results are reliable. Edge detection may also be an effective indication. In our approach, we take the uncertainty map given by [Bae et al. 2021]. We feed the image \(I_i\) into [Bae et al. 2021] and obtain the normal estimation \(\hat{N}_i^{raw}\) and corresponding uncertainty \(U_i\). Then, we use uncertainty as an indication to filter \(\hat{N}_i^{raw}\) to obtain a reliable estimation result \(N_i\):

\[
N_i = \hat{N}_i^{raw} \cdot \text{Bool}(U_i \leq \text{mean}(U_i)).
\]

We take the mean value of \(U_i\) as the threshold to filter \(\hat{N}_i^{raw}\) and obtain a reliable estimation result \(N_i\). We also set a zero value for pixels where the normal is filtered. We use \(N_i\) as a normal prior to guide the optimization of NeuralRoom. In addition, the normal prior is also used in the perturbation-residual training method.

### 4.2 NeuralRoom Module

**NeuralRoom Rendering Method.** Our NeuralRoom renderer follows the basic volume rendering model Neus [Wang et al. 2021b] while integrating additional prior information and the perturbation-residual restriction.

NeuralRoom uses two multilayer perceptrons (MLPs) to represent geometry \(f\) and color functions \(c\). The geometry function \(f : \mathbb{R}^3 \rightarrow \mathbb{R}\) maps point \(x \in \mathbb{R}^3\) to the signed distance to the object. The color function \(c : \mathbb{R}^3 \times S^2 \rightarrow \mathbb{R}^3\) maps a point position \(x \in \mathbb{R}^3\) and a viewing direction \(v \in S^2\) to the RGB color space. The surface \(S\) of the object is represented by the zero set of its signed distance function (SDF): \(S = \{ x \in \mathbb{R}^3 | f(x) = 0 \}\).

As a volume rendering method, the NeuralRoom renderer represents scenes as a colorized volume with weights and integrates radiation along with rays via alpha blending. Each pixel determines a ray. This scheme samples \(n\) points along the ray \(r = [x_i = o + t_i v] | t_i = 1, 2, ..., n, t_i \leq t_{i+1}\), \(o\) is the position from which the ray is emitted, which is usually the center of the camera, \(v\) is the direction of the ray, \(t\) is the length of the ray that has been emitted.

Substituting a query spatial position \(x_i\) into the geometry function \(f\), an SDF estimation should be \(f(x_i)\). Then, a unimodal density distribution function \(\phi_s(f(x_i))\) is introduced. \(\phi_s(f(x_i)) = se^{-sx_i}/(1 + e^{-sx_i})^2\) which is the derivative of the sigmoid function \(\Phi_s(x_i) = (1 + e^{-sx_i})^{-1}\), \(s\) is a learnable parameter. The discrete opacity values \(\alpha\) are shown to be:

\[
\alpha_i = \max\left(\frac{\Phi_s(f(x_i) - \Phi_s(f(x_{i+1})))}{\Phi_s(f(x_i))}, 0\right).
\]

The scheme approximates the color, normal, and length of this ray by calculating:

\[
\hat{C}(r) = \sum_{i=1}^{n} M_i \alpha_i c(x_i, v),
\]

\[
D(r) = \sum_{i=1}^{n} M_i \alpha_i t_i,
\]
\[ \hat{N}(v) = \sum_{i=1}^{n} M_i \alpha \text{gradient}(\xi_i), \]

where \( M_i = \prod_{j=1}^{i-1} (1 - \alpha_j) \) indicates the accumulated transmittance, \( \alpha_i \) is the per-voxel opacity value acquired from implicit geometry function \( f \), and \( \hat{C}, \hat{D}, \hat{N} \) represent rendering color, rendering depth and rendering normal respectively. The derivative of implicit geometric function \( f \) with respect to the three coordinate directions at point \( p_j: (\frac{df}{dx}, \frac{df}{dy}, \frac{df}{dz}) \) is the gradient at that position. The derivation process is completed by PyTorch’s automatic derivation [Paszke et al. 2019].

**Guided Optimization.** Let \( p \) be the 2D pixel coordinate in \( I_i \). To optimize NeuralRoom, we first sample some pixels from a specific image \( I_i \) and generate their corresponding rays in world space 
\[ P = [C_i(p), D_i(p), N_i(p), o_i, v_i(p)], \]
where \( C_i \) is the color of the pixel acquired from \( I_i \), \( D_i \) is the corresponding distance prior, which is the length between the camera center and the intersection of the ray and implicit surface to consist of the distance prior. \( N_i \) is the normal corresponding to the sampling ray, \( o_i \) and \( v_i \) are the coordinate direction of the ray, \( o_i \) and \( v_i \) are calculated from \( K_i \) and \( T^{pp} \). We assume that the batch size of sampling rays is \( k \), and we sample \( n \) points along each ray.

As a rendering-based neural surface reconstruction method, its most important loss function is to minimize the difference between the rendered pixel colors and the ground truth input corresponding pixel colors:
\[ L_{\text{color}} = \frac{1}{k} \sum_{k} |\hat{C}_{ik} - C_k|, \]

where \( C_k \) is the corresponding pixel color, \( \hat{C}_{ik} \) is the corresponding rendering color.

**Prior Loss.** The prior loss \( L_{\text{prior}} \) consists of two parts, the distance prior loss \( L_{\text{prior}, D} \) and the normal prior loss \( L_{\text{prior}, N} \):
\[ L_{\text{prior}} = L_{\text{prior}, D} + \gamma L_{\text{prior}, N}. \]

We force the distance \( \hat{D}_{ik} \) between the camera center and the intersection of the ray and implicit surface to consist of the distance prior \( D_k \). If a sampled ray has a corresponding distance prior, we perform the distance prior loss to constrain the intersection to a specific position:
\[ L_{\text{prior}, D} = \frac{1}{n} \sum_{j=1}^{n} \text{SmoothL1}(\hat{D}_{ik} - D_k), \]

\[ \text{SmoothL1}(A, B) = \begin{cases} 
0.5 \times |A - B|^2 / \beta, & ||A - B|| <= \beta, \\
||A - B|| - 0.5 \times \beta & ||A - B|| > \beta,
\end{cases} \]

where \( \hat{D}_{ik} \) is the rendered depth if the pixel has a distance prior, \( A \) and \( B \) are two vectors of the same dimension used to illustrate \( \text{SmoothL1} \), \( \text{SmoothL1} \) is the smooth L1 loss \( (\beta = 0.1) \), \( D_k \) is the corresponding distance prior, and \( n \) is the number of rays that have a distance prior. Therefore, the intersection positions between these rays and the implicit surface are consistent with the distance prior. The distance prior makes the reconstruction results consistent with the MVS results in texture-rich areas and where the surface geometry changes sharply. In addition, since the rendering loss is dominant in the optimization process, this will reduce the impact of outliers in MVS results on reconstruction.

Next, we need to solve the most important problem of indoor reconstruction: shape-radiance ambiguity in the texture-less region. The normal prior loss is:
\[ L_{\text{prior}, N} = \frac{1}{n} \sum_{j=1}^{n} \text{SmoothL1}(\hat{N}_{ik} - N_k). \]

Although we use two priors to guide the optimization, still we face some problems. One is that the depth and normal estimation results always have noise. Another is that the normal estimation of a region may be inconsistent. The inaccurate camera pose, unstable light condition and poor photo imaging quality easily cause the above situation.

The derivative of geometric network \( f \) at the sample point is the normal of that position. The normal obtained by this computing method is a very local constraint. Because the sampling ray is discrete and random, the normal condition can only ensure that the normal corresponding to the sampling ray is consistent with the prior and cannot affect a larger neighborhood. The rendered color loss cannot play an effective role in the texture-less region, and the distance prior generally cannot be obtained by MVS. At the same time, the normal prior can not uniquely determine a spatial location, resulting in the optimized surface geometry fluctuating and even breaking into many parts.

A natural solution, which may be the best, is to render the depth and normal of all rays in a patch from the net \( f \) to give geometric
constraints. However, each sampling ray needs to query the network hundreds of times to obtain the data required for rendering. Moreover, rendering everything in a patch will consume considerable memory and computing time. Therefore, we propose a compromise approach called perturbation-residual restriction to establish connections between sampling rays, making the reconstructed surface continuous.

The perturbation-residual restrictions assume that in a small region, the sampling points should have the same normal, and the distances to the camera center should be similar. We divide each optimization step into two stages. In the first stage, we randomly sample $k$ rays as before and render their color $\hat{C}$, depth $\hat{D}$ and normal $\hat{N}$. In the next stage, we perturb the ray direction. With the new sampling ray $P = (v_k, v^\text{pert}_k)$, we query the net $f$ again and render the corresponding depth $\hat{D}^\text{pert}$ and normal $\hat{N}^\text{pert}$. Then the residual is calculated with the first stage. The ray direction corresponding to a pixel $p_k : (u, v) \in I_i$ in the world coordinate is

\[
\begin{align*}
\v_k &= R_i^{-1} \text{Normalize}(K_i^{-1} \begin{pmatrix} u \\ v \end{pmatrix}), \quad (14) \\
\v^\text{pert}_k &= R_i^{-1} \text{Normalize}(K_i^{-1} \begin{pmatrix} u + (a - 0.5) * w \\ v + (b - 0.5) * w \end{pmatrix}), \quad (15)
\end{align*}
\]

where $K_i$ is the intrinsic matrix of $I_i$, $R_i$ is the rotation matrix belonging to the extrinsic matrix $T_i$. $\text{Normalize}$ is the normalization function that normalizes the length of the vector to be 1, random variables $a, b \sim U[0, 1]$ obey the uniform distribution on $[0, 1]$, and $w$ is a hyperparameter indicating the amplitude of perturbation. The perturbation-residual restrictions establish the connection between surrounding rays to share their geometric information. Then, we calculate the residual with the previous stage:

\[
\begin{align*}
L_{\text{res}} &= \delta L_{\text{smooth,D}} + \epsilon L_{\text{consist,N}}, \quad (16) \\
L_{\text{smooth,D}} &= \frac{1}{k} \sum_k \text{SmoothL1}(\hat{D}_k, \hat{D}^\text{pert}_k), \quad (17) \\
L_{\text{consist,N}} &= \frac{1}{N_{\text{prior,N}}} \sum_k \text{SmoothL1}(N_k, N^\text{pert}_k), \quad (18)
\end{align*}
\]

where $\text{SmoothL1}$ is the smooth L1 loss ($\beta = 0.1$) defined in Equation 12, $N_{\text{prior,N}}$ is the number of valid $N_k$. $\delta$ and $\epsilon$ are two hyperparameters. $L_{\text{smooth,D}}$ is a smoothing term. This term works on all sampling rays, aiming to make the depth of the sampling ray and the corresponding perturbation ray close. If $N_i$ has a valid value, then $N^\text{pert}_k$ would be constrained by $L_{\text{consist,N}}$. These two optimization terms make the surface geometry in the flat region continuous and obey the normal prior.

The final loss function is defined as

\[
\begin{align*}
L &= L_{\text{color}} + L_{\text{prior}} + L_{\text{res}} + L_{\text{Eikonal}}, \quad (19) \\
L_{\text{Eikonal}} &= \frac{1}{nk} \sum_{n,k} (|\nabla f(x_{n,k})| - 1)^2, \quad (20)
\end{align*}
\]

where $L_{\text{Eikonal}}$ is the Eikonal term on the sampling points to regularize the SDF.

4.4 Mesh Extraction

For each spatial position in the optimization area, we query the geometry function $f$ to obtain the corresponding TSDF value. Then, we use marching cube [Lorensen and Cline 1987] to extract the raw mesh. There are many positions we do not need in the raw mesh, so we conduct ray-tracing to obtain the depth map for each pose and perform TSDF fusion [Curless and Levoy 1996; Newcombe et al. 2011] to generate our final mesh model. Ray-tracing and TSDF fusion are implemented based on Open3D [Zhou et al. 2018].

5 EXPERIMENT

5.1 Experimental Setup

Dataset. We evaluate our approach and baseline methods on the indoor dataset, ScanNet (V2) [Dai et al. 2017]. We randomly select 8 test scenes from the intersection of the test set of Frament [Huang et al. 2019] and ScanNet [Dai et al. 2017]. The [Bae et al. 2021] network has been pretrained on the training set of [Huang et al. 2019] for evaluation. We take one photo out of approximately every ten adjacent photos with an image resolution of 1296 × 968.

Implementation Details. The geometry function $f$ is modeled by an MLP, which consists of 8 hidden layers with a hidden size of 256. The color function $c$ is modeled by an MLP, which consists of 4 hidden layers with a size of 256. Positional encoding, initialization of the implicit neural representation, and coarse to fine sampling methods are similar to the method of [Wang et al. 2021b]. The numbers of coarse and fine sampling points for each ray are 64 and 64, respectively. We sample 512 rays per batch and train NeuralRoom for 200k iterations on a single NVIDIA RTX2080Ti GPU. The hyperparameters used in the experiment are as follows: $\epsilon = 1.3, w = 2.4, \gamma = 0.001, \delta = 0.001$, and $\epsilon = 0.001$.

Baselines. We do not compare our method with rendering-based reconstruction methods [Oechsle et al. 2021; Wang et al. 2021b; Yariv et al. 2021] since these reconstruction methods often fail. We compare our method with the following baseline methods, NeuralRecon [Sun et al. 2021a] and Atlas [Murez et al. 2020], two volumetric multiview indoor scene reconstruction methods that directly extract 3D surface from feature volume; COLMAP [Schoenberger and Frahm 2016] and ACMP [Xu and Tao 2020b], two traditional PatchMatch-based MVS methods; 3DVNet [Rich et al. 2021], a learning-based multiview stereo method that combines the advantages of depth-based and volumetric multiview stereo approaches; and ESTDepth [Long et al. 2021b], a learning-based multiview depth estimation method.

Evaluation Protocols. We choose a mesh as the 3D geometry representation for qualitative comparison and quantitative evaluation. For COLMAP, we perform Delaunay triangulation to form a mesh from a point cloud. For our method, Atlas, NeuralRecon and COLMAP with Delaunay triangulation, in which there are a large number of nonobservation areas. Therefore, we use ray tracing provided by Open3D [Zhou et al. 2018] on the reconstructed model to obtain the depth map of each view. Then we use TSDF fusion [Curless and Levoy 1996; Newcombe et al. 2011] to obtain a trimmed 3D mesh. For ACMP, ESTDepth and 3DVNet, we use TSDF fusion to
obtain a mesh. The voxel length is 0.02m, and the SDF truncation value is 0.12m. For quantitative evaluation, we use a regular voxel grid to create a uniformly downsampled point cloud from the input mesh. The side length of the voxel grid is 0.005m. The threshold of precision and recall is 0.05m.

5.2 Geometry Prior Statistics
We perform the quantitative evaluation for the prior on all test scenes. The distance prior is converted from the corresponding MVS depth map, so we evaluate the depth map instead. The depth map and normal map are evaluated in Table 1 and Table 2. The evaluation of the normal map filtered by uncertainty has a 50 extension. After filtering, we obtain highly accurate normal estimation results, for which the mean angle error is 8.183°.

| Comp | Abs Diff | Abs Rel | Sq Rel | RMSE |
|------|----------|---------|--------|------|
| 0.143| 0.093    | 0.042   | 0.013  | 0.158|

Table 1. Quantitative evaluation of the depth map acquired by COLMAP.
Table 2. Quantitative evaluation of the acquired normal map. The filtered normal maps are with a _50 extension.

|        | Mean | Median | RMSE | Mean_50 | Median_50 | RMSE_50 |
|--------|------|--------|------|---------|-----------|---------|
|        | 14.691 | 7.329 | 23.224 | 8.183 | 4.931 | 13.030 |

5.3 Evaluation Results

We provide qualitative and quantitative comparisons on the ScanNet dataset to evaluate the performance of our system. Our method achieves state-of-the-art both quantitatively and qualitatively. Since all algorithms will produce some additional reconstruction areas, for a fair comparison, we perform ray tracing with ground truth camera parameters to get the corresponding depth, and then perform TSDF fusion to acquire cleaned 3D reconstruction.

**Visual comparison.** Figure 7 shows our full scene and detailed visualization results compared with those of different reconstruction methods, including COLMAP [Schonberger and Frahm 2016], Atlas [Murez et al. 2020], NeuralRecon [Sun et al. 2021a], 3DVNet [Rich et al. 2021], ESTDepth [Long et al. 2021b] and ground truth [Dai et al. 2017].

**Quantitative comparison.** Table 3 reports the summary of 3D geometry metrics for different methods. Since rendering-based reconstruction methods have a high probability that the satisfactory reconstruction of indoor scenes cannot be acquired through input images (Figure 2), we only evaluate the methods mentioned above 5.1.

Our method has a relatively balanced performance in accuracy and completeness. The overall performance is much better than that of other different types of methods. We believe that the improvements come from the following aspects:

Table 3. Quantitative evaluation of reconstruction with existing methods on the ScanNet dataset. We report the average results for eight scenes from the test set.

| Method   | Prec↑ | Recall↑ | F-score↑ | Acc↓ | Comp↓ | Overall↓ |
|----------|-------|---------|----------|------|-------|----------|
| COLMAP   | 45.136 | 44.510 | 44.678   | 0.108 | 0.136 | 0.122    |
| ACMP     | 35.978 | 70.691 | 47.622   | 0.152 | 0.047 | 0.100    |
| ESTDepth | 38.217 | 50.992 | 43.589   | 0.144 | 0.075 | 0.110    |
| 3DVNet   | 64.961 | 64.562 | 64.665   | 0.071 | 0.061 | 0.066    |
| Atlas    | 67.957 | 57.747 | 61.871   | 0.050 | 0.090 | 0.070    |
| NeuralRecon | 63.851 | 47.401 | 54.208   | 0.054 | 0.128 | 0.091    |
| Ours     | 68.347 | 65.298 | 66.756   | 0.051 | 0.058 | 0.055    |

**Distance prior.** The distance prior guides the implicit surface close to the corresponding point, which gives the NeuralRoom the ability to preserve the reliable spatial information. The weight of the distance prior loss in optimization can be adjusted according to its quality.

**Normal prior.** The normal prior is the most important prior. With a normal prior, NeuralRoom can make the surface normal of the
texture-less region consistent. This leads to better visual effects and quantitative evaluation. The weight of the normal prior loss in optimization can also be adjusted according to its quality.

Perturbation-residual restrictions. The perturbation-residual restrictions ensure the continuity of the reconstructed scene and improve the accuracy and completeness. It establishes a connection between the sampling ray and the corresponding auxiliary ray.

Differentiable renderer. The key to combining the above three aspects is our NeuralRoom differentiable renderer. The reliable priors reduce the possible spatial variation range of an implicit neural surface which helps the NeuralRoom alleviate shape-radiance ambiguity. The renderer takes the color loss as a primary loss to optimize an implicit neural surface that can render an image consistent with the input training images. In addition, the renderer has the ability to resist the influence caused by incorrect geometric priors. Similar to volumetric methods [Murez et al. 2020; Sun et al. 2021a], the renderer considers the influence of all inputs in the reconstruction optimization, while the depth estimation method usually only considers the neighborhood.

5.4 Ablation Study
To better understand the role of each optimization item, we performed ablation studies over each component of the proposed system. The experiment was conducted on Scene0801_00 in ScanNet. Some simple scenes like that can be reconstructed without a bounding box and are sensitive to each loss term. The qualitative evaluation is shown in Figure 9, and the quantitative evaluation is shown in Table 4. In addition, we also perform an ablation study on the complex real-world scene, please refer to the supplementary document.

Table 4. Ablation study. We test the effect of each loss function in the method. This analysis shows that our full method performs best both visually and quantitatively.

| Method          | Comp↓ | Acc↓ | Overall↓ |
|-----------------|-------|------|----------|
| a Base          | 0.055 | 0.157| 0.106    |
| b Base + Distance prior | 0.048 | 0.095| 0.072    |
| c Base + Normal prior | 0.050 | 0.059| 0.054    |
| d Base + Prior  | 0.031 | 0.050| 0.041    |
| e Base + Prior + Smooth | 0.033 | 0.054| 0.044    |
| f Base + Prior + Consist | 0.027 | 0.041| 0.034    |
| g Full          | 0.022 | 0.027| 0.024    |

The distance prior $L_{prior_D}$ provides accurate 3D points, which helps improve the accuracy of the reconstruction. The rich textured and edge areas are well reconstructed. The normal prior $L_{prior_N}$ is the most important term of our system, which can significantly improve the completeness and accuracy of the scene. When both $L_{prior_D}$ and $L_{prior_N}$ simultaneously participate in optimization,
the reconstruction accuracy and completeness are further improved. There are cracks in texture-less areas, although the quantitative results are better than before. The noise that exists in the priors and the lack of distance prior may cause this phenomenon. The residual-perturbation restrictions \( L_{\text{smooth}} \) and \( L_{\text{consist}} \) establish a connection between the sampling ray and its corresponding auxiliary ray, which improves the reconstruction quality of the surface. Using \( L_{\text{consist}} \) alone can improve the completeness and accuracy, but more cracks appear in the scene. The normal of two points far apart in space can also be consistent, so only considering the normal constraint cannot determine a unique position in space. The \( L_{\text{smooth}} \) term is used to limit the spatial distance between two points, which is designed to smooth the scene. When both local normal and smooth constraints are added to the optimization, we can obtain a better visual effect and quantitative evaluation result. In addition, we can adjust the corresponding weight according to the quality of the prior, so as to obtain a better reconstruction result.

5.5 Advantages and Limitation

The depth sensor emitting infrared rays has difficulty to collect the depth information of the mirror, black area and distant objects, which results in incomplete reconstruction. NeuralRoom takes RGB images as input, which can restore this part of the scene (Figure 10 left). However, there are several limitations of the proposed method.

**Poses and priors.** Almost all rendering-based reconstruction methods rely on the accurate camera pose. Therefore, large poses and priors errors have a strong adverse impact on reconstruction results. In addition, when the two surfaces with the same normal are close to each other, if the correct distance prior is missing, the NeuralRoom will over smooth them (Figure 10, right). Using more advanced learning-based pose, depth and normal estimation methods to provide more reliable geometry priors and camera poses can ensure the reconstruction quality.

**Computational cost.** Our method requires a large amount of computational resources for geometry prior computation and neural representation training. Accelerating with an updated differentiable rendering [Müller et al. 2022; Yu et al. 2021] architecture is a direction for improvement. Moreover, using a neural network such as [Murez et al. 2020] to quickly reconstruct a structure of the scene and then using a differentiable renderer or other learning-based methods to adjust the details of the indoor scene may be a good solution.

5.6 Advanced NeuralRoom

We use more advanced indoor scene reconstruction algorithms [Murez et al. 2020; Rich et al. 2021; Sun et al. 2021a] instead of COLMAP [Schonberger and Frahm 2016] to provide distance priors, and show the improved reconstruction quality of these algorithms achieved by our proposed NeuralRoom system.

![Advantages and limitations](image)

**Fig. 10.** Advantages and limitations.

![Comparison of reconstruction quality](image)

**Fig. 11.** The improvement of reconstruction quality of different reconstruction algorithms by our proposed NeuralRoom system.

| Method       | Prec↑ | Recall↑ | F-score↑ | Acc↓ | Comp↓ | Overall↓ |
|--------------|-------|---------|----------|------|-------|----------|
| NeuralRoom   | 68.347| 65.298  | 66.756   | 0.051| 0.058 | 0.055    |
| NR-Atlas     | 73.003| 69.062  | 70.948   | 0.044| 0.052 | 0.048    |
| NR-NeuralRecon| 69.977| 66.965  | 68.393   | 0.054| 0.059 | 0.056    |
| NR-3DVNet    | 73.339| 70.496  | 71.865   | 0.046| 0.051 | 0.048    |

These learning-based multiview reconstruction algorithms provide a distance prior with higher accuracy or better completeness than COLMAP [Schonberger and Frahm 2016], which will help further alleviate shape-radiance ambiguity resulting in better reconstructions. Table 5 shows the quantitative evaluation and Figure 11 shows the qualitative comparisons, the related algorithms improved by NeuralRoom have an NR- prefix. In addition to replacing the distance prior module in NeuralRoom, researchers can further improve the reconstruction quality by replacing the normal estimation module and differentiable renderer with their own more advanced algorithms.

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6 CONCLUSIONS
We have presented NeuralRoom, a rendering-based neural surface reconstruction method for reconstructing indoor scenes directly from a set of 2D images. The key to successful indoor scene reconstruction by using differentiable rendering is that we find complementarity between depth estimation and normal estimation methods, which helps alleviate inherent shape-radiance ambiguity. We also have designed geometric constraints for the renderer to obtain a smoothing and complete surface reconstruction. NeuralRoom produces impressive reconstruction and successfully reconstructs the surface with no texture or rich texture. In addition, we show the reconstruction improvement of existing multiview reconstruction algorithms by incorporating NeuralRoom pipeline.

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