Worldsheet: Wrapping the World in a 3D Sheet for View Synthesis from a Single Image

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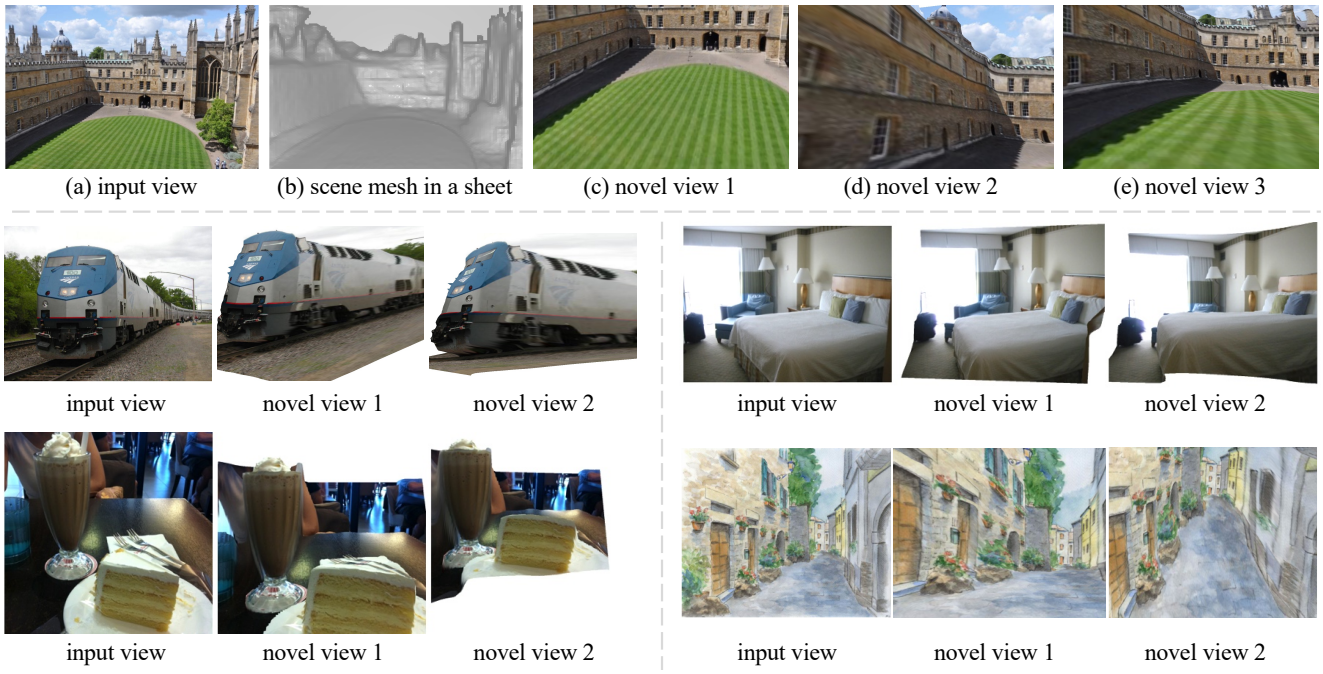


Figure 1: We synthesize novel views from large view-point changes given a single input RGB image (shown in a) by wrapping a mesh sheet (shown in b) onto the image, and rendering it from novel view-points (shown in c, d, e). Plausible novel views are generated for outdoor scenes, outdoor objects, indoor scenes, indoor objects and even paintings with high resolution (960×960) input. Please see continuously synthesized views at worldsheet.github.io. (Image sources: [44, 11, 22, 25])

Abstract

We present Worldsheet, a method for novel view synthesis using just a single RGB image as input. This is a challenging problem as it requires an understanding of the 3D geometry of the scene as well as texture mapping to generate both visible and occluded regions from new view-points. Our main insight is that simply shrink-wrapping a planar mesh sheet onto the input image, consistent with the learned intermediate depth, captures underlying geometry sufficient enough to generate photorealistic unseen views with arbitrarily large view-point changes. To operationalize this, we propose a novel differentiable texture sampler that allows our wrapped mesh sheet to be textured; which is then transformed into a target image via differentiable rendering. Our approach is category-agnostic, end-to-end trainable without using any 3D supervision and requires a single image at test time. Worldsheet consistently outperforms prior state-of-the-art methods on single-image view synthesis across several datasets. Furthermore, this simple idea captures novel views surprisingly well on a wide range of high resolution in-the-wild images in converting them into a navigable 3D pop-up. Video results and code at https://worldsheet.github.io

1. Introduction

A 2D image is the projection of an underlying 3D world, but we as humans have no trouble in understanding this structure and imagining how an image will look from other

views. Consider the train shown in Figure 1, the reason we can seamlessly predict its other views just from a single image is because of the abstractions we have learned from past experience of watching several trains, or similar shaped objects from different views. Enabling machines with such an ability to reason about 3D from a single image will bring trillions of still photos to life with several applications in virtual reality, animation, image editing, and robotics.

This goal of synthesizing novel views from 2D images has been pursued for decades, from early efforts relying completely on geometry [7, 54, 35] to more recent learning based approaches [52, 40, 1, 27, 23, 32]. Over the years, significant progress has been made in this direction. However, although generating impressive photorealistic output views, most of these previous approaches require multiple images or ground-truth depth at test time, which severely hinders their practicality as a general tool.

On the other hand, the holy grail of developing a general-purpose tool to convert any arbitrary single image into a corresponding 3D structure for generating novel views has kept the community hooked for years. To compensate for the lack of multiple views or 3D models at test time, methods on single-image 3D rely on statistical learning from data. This line of work can be traced back to classic works of Hoiem *et al*. [11], followed by Saxena *et al*. [34], to obtain 'qualitative 3D' from a single image by marrying geometry and learning to see images as a collection of planes.

An ideal approach to general-purpose view synthesis should not only rely on a single image at test time, but also learn from easy-to-collect supervision at training. In the deep learning era, there is growing interest in end-to-end methods with intermediate 3D representations supervised by multiple images and no explicit 3D information during training. However, they are mostly applied to objects [18, 42, 48, 13, 39] and not scenes, and are either category-specific, applied to synthetic scenes, or both. Recent works [5, 47, 43] alleviate this issue by training with multiple views of real-world scenes, relying on point cloud or multiplane images as intermediate representations. However, multiplane images are mostly good for small view-point changes as each plane is at a constant depth, and for point cloud, one needs to represent each point in a scene individually, making it inefficient to scale to high-res data or large view-point changes. In contrast, meshes provide a sparser scene representation, *e.g*., a single mesh face can theoretically represent the whole flat surface of a wall, making it ideal for single-image view synthesis. However, mesh recovery from single images has been studied mostly for object images and in a category-specific manner [2, 13, 17].

In this paper, we present an end-to-end approach for novel view synthesis from *a single image* via an intermediate *mesh representation*. Unlike mesh reconstruction for objects of certain categories, generating meshes for a scene is challenging as there is no notion of mean or canonical shape to start from, or silhouette from segmentation for supervision. We side-step this problem by wrapping by a deformable mesh sheet over the 3D world – much like wrapping a 2D tinfoil onto a 3D pan before baking! We name this shrink-wrapped mesh *Worldsheet*, a term borrowed from physics for the 2D manifold of high-dimensional strings. After generating this Worldsheet for a given view, novel views are obtained by moving the camera in 3D geometry space (Figure 2), which allows us to train from just two views of a scene *without any 3D or depth supervision*.

To train our model end-to-end, reconstructing mesh texture from inputs and rendering it in novel views both need to be differentiable. Latter is easily handled thanks to recent differentiable mesh renderers [14, 24, 31]. To address the former, we propose a differentiable texture sampler over projected 2D views, enabling gradient computation of the reconstructed texture map over the 3D mesh geometry.

Worldsheet allows generating novel views from a single image with large view-point changes. It consistently outperforms prior state-of-the-art by a significant margin on three benchmark datasets (Matterport [3], Replica [41], and RealEstate10K [52]) and is applicable to very high-resolution images in-the-wild as shown in Figure 1.

2. Related work

Novel view synthesis from multiple images. Traditionally, novel view synthesis used multiple input views at test time [4, 20, 9], and are often based on different representations. Among recent works, Waechter *et al*. [45] build scene meshes with diffuse appearance. StereoMag [52] proposes multiplane images (MPIs) from a stereo image pair as a layered scene representation. NPBG [1] captures the scene as a point cloud with neural descriptors. NeRF [27] proposes a neural radiance field representation for scene appearance. NSVF [23] adopts sparse voxel octrees as scene representations. FVS [32] uses recurrent mapping and blending based on depth map of the scene from multi-view stereo. Yoon *et al*. [49] combine depth from both single and multiple views to generate novel views of dynamic scenes. Access to multiple input views greatly simplifies the task, allowing the scene geometry to be recovered via multi-view stereo [35].

Novel view synthesis from a single image. In early works, Debevec *et al*. [7] recover 3D scene models and Horry *et al*. [12] fit a regular mesh to generate novel views. Liebowitz *et al*. [21] and Criminsi *et al*. [6] generate meshes via projective geometry constraints. These methods came at the expense of manual editing until Hoiem *et al*. [11] generate automatic 3D pop-up from 2D images based on vertical and ground planes. More recently in [29, 16, 36], layered depth images are used for single image view synthesis based on a pretrained depth estimator. In [43], online videos

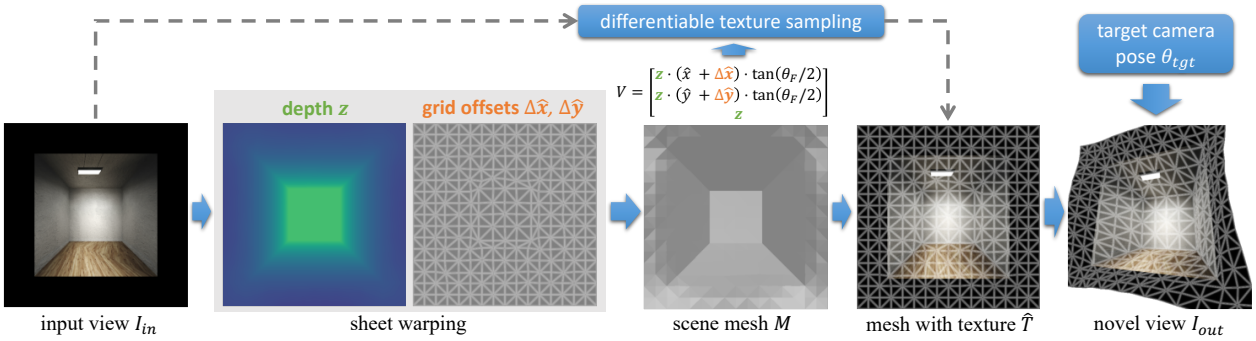


Figure 2: An overview of our *Worldsheet* approach. Given an input view I_{in}, we build a scene mesh by warping a $W_m \times H_m$ grid sheet onto the scene geometry via grid offset $(\Delta\hat{x}, \Delta\hat{y})$ and depth z (Sec. 3.1). Then, we sample the UV texture map $\hat{T}$ of the scene mesh differentiably (Sec. 3.2) and render it from the target camera pose to output a novel view I_{out}. Our mesh warping is learned end-to-end using the losses on the novel view (Sec. 3.3). We further apply an inpainting network over I_{out} (not shown above; see Sec. 3.4) to inpaint invisible regions and refine image details, outputting a refined novel view I_{paint}. We train with two views without any 3D or depth supervision and require just a single RGB image at test time.

are used to train scale-invariant MPI representation for view synthesis. SynSin [47] synthesizes novel views from a single image with a feature point cloud. We follow the same experimental setup as SynSin but learns to construct scene meshes instead of point clouds as scene representations to generate novel views from large viewpoint changes.

Differentiable mesh rendering. Recent work on differentiable mesh renders [14, 24, 31] allow learning 3D structures through synthesis. NMR [14] and SoftRas [24] reconstruct the 3D object shape as a mesh by rendering it, comparing it with the input image, and back-propagating losses to refine the mesh geometry. CMR [13], CSM [17] and U-CMR [8] build category-specific object meshes from images by deforming from a mean or template category shape through silhouette (and keypoints in [13]) supervision.

Our method is aligned with the analysis-by-synthesis paradigm above. However, unlike most previous works that apply differentiable mesh rendering to objects, we learn the 3D geometry of *scenes* through the rendering losses on the novel view. Moreover, instead of predicting a texture flow as in [13, 8], we propose to analytically sample the mesh texture from the input view with a differentiable texture sampler. Unlike [30], our differentiable texture sampler considers multiple mesh faces in the z-buffer (soft rasterization instead of only the closest one), and assumes perspective (instead of orthographic) camera projection.

3. Worldsheet: Rendering the World in a Sheet

In this work, we propose *Worldsheet* to synthesize novel views from a single image, as shown in Figure 2. Given an input image I_{in}, we build a 3D scene mesh M by warping a lattice grid (*i.e.* a "sheet") onto the scene geometry through depth and grid offset, and sample the mesh's UV texture map in a differentiable manner. We then render the mesh from the target camera pose to output the novel view image I_{out}. We further apply an inpainting network over the rendered mesh to imagine the invisible regions, outputting a 2D image I_{paint} as the final target view prediction. Our model is trained with only losses over the 2D output image of the target view, *without any 3D or depth supervision*.

3.1. Scene mesh prediction by warping a sheet

From the input view image I_{in} of size $W_{im} \times H_{im}$, we build a scene mesh by warping a $W_m \times H_m$ lattice grid (*i.e.* a sheet) onto the scene, as shown in Figure 2. We first extract a $W_m \times H_m$ visual feature map $\{q_{w,h}\}$ from I_{in} with a convolutional neural network. Each $q_{w,h}$ is a feature vector at spatial location (w, h) on the $W_m \times H_m$ network output. In our implementation, we use ResNet-50 [10] (pretrained on ImageNet) with dilation [50] to output features $\{q_{w,h}\}$.

From each $q_{w,h}$ on the feature map, we predict the grid offset $\Delta\hat{x}_{w,h}$ and $\Delta\hat{y}_{w,h}$ to decide how much the vertex (w, h) on the grid should move away from its anchor positions within the image plane (we output $\Delta\hat{x}_{w,h}$ and $\Delta\hat{y}_{w,h}$ in NDC space [37] between -1 to 1). We also predict how far each vertex is from the camera, *i.e.* its depth $z_{w,h}$. These values are predicted using learned linear mappings as

$$\Delta\hat{x}_{w,h} = \tanh\left(W_1 q_{w,h} + b_1\right)/(W_m - 1) \quad (1)$$

$$\Delta\hat{y}_{w,h} = \tanh\left(W_2 q_{w,h} + b_2\right)/(H_m - 1) \quad (2)$$

$$z_{w,h} = g\left(W_3 q_{w,h} + b_3\right) \quad (3)$$

where division by $(W_m - 1)$ and $(H_m - 1)$ ensures that the vertices can only move within a certain range. $g(\cdot)$ is a scalar nonlinear function to scale the network prediction into depth values. We use $g(\psi) = \alpha_g/(\sigma(\psi) + \epsilon_g) + \beta_g$ in our implementation, where $\sigma(\cdot)$ is the sigmoid function and α_g, β_g and ϵ_g are fixed hyper-parameters.

Building the 3D scene mesh. We first build the mesh vertices $\{V_{w,h}\}$ from the grid offset and depth as

$$V_{w,h} = \begin{bmatrix} z_{w,h} \cdot (\hat{x}_{w,h} + \Delta\hat{x}_{w,h}) \cdot \tan(\theta_F/2) \\ z_{w,h} \cdot (\hat{y}_{w,h} + \Delta\hat{y}_{w,h}) \cdot \tan(\theta_F/2) \\ z_{w,h} \end{bmatrix} \quad (4)$$

for $w = 1, \cdots, W_m$ and $h = 1, \cdots, H_m$. Here θ_F is the camera field-of-view, and $\hat{x}_{w,h}$ and $\hat{y}_{w,h}$ are anchor positions on the grid equally spaced from -1 to 1.

Then, we connect the mesh vertices $\{V_{w,h}\}$ along the edges on the grid to form mesh faces $\{F\}$ as shown in Figure 2 and obtain a 3D mesh $M = (\{V_{w,h}\}, \{F\})$. A vertex in the mesh is connected to its 4 or 8 neighbours on the grid.

Regularization. The predicted scene mesh is regularized with two losses. First, we apply an L2 regularization term $L_g = \sum_{w,h} \left(\Delta\hat{x}^2_{w,h} + \Delta\hat{y}^2_{w,h} \right)$ to the grid offset to avoid unnecessary large grid deformations. To encourage the mesh surface to be smooth unless it needs to bend to fit the scene geometry, we also apply a Laplacian term $L_m = \sum_{w,h} \left\| \sum_{(\bar{w},\bar{h}) \in N(w,h)} \left(V_{\bar{w},\bar{h}} - V_{w,h} \right) \right\|_1$ on the mesh vertices, where $N(w,h)$ are the adjacent vertices to (w,h).

3.2. Differentiable texture sampler

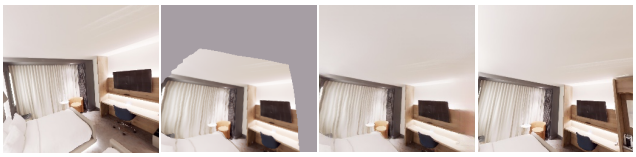
To render the mesh in another camera pose for novel view synthesis, we would like to reconstruct its texture from the scene appearance in the input view. While a few approaches [13, 8] build mesh texture with a learned texture flow on objects, it is hard to apply the same to scenes, which are unlike birds or cats and do not have canonical shapes. In this work, we take an alternative route and propose a differentiable texture sampler. We *analytically* sample the mesh texture $\hat{T}$ as a UV texture map [37] from the input view I_{in}, where gradients $\partial\hat{T}/\partial V$ and $\partial\hat{T}/\partial I_{in}$ over the vertex coordinates and the input image can be computed.

To implement this texture sampler, we first build a z-buffer containing top K mesh faces on each image pixel (i,j) as in PyTorch3D [31], and splat the RGB pixel intensities from the image I_{in} onto the UV texture map $\hat{T}$. Specifically, we compute the blending probability $p^k_{i,j}$ for the k-th covering mesh face (sorted in ascending z-order in the z-buffer) on pixel (i,j) based on the softmax RGB blend in [31] as $p^k_{i,j} = D^k_{i,j} \cdot \exp(-Z^k_{i,j}) / \sum_{k'} D^{k'}_{i,j} \cdot \exp(-Z^{k'}_{i,j})$, where $D^k_{i,j}$ is the soft-rasterization probability map [24] of the k-th face on the image (nearly 0 outside the face, nearly 1 inside the face, and blurry on the edges; see Figure 4 in Liu *et al*. [24]), and $Z^k_{i,j}$ is the depth value of the 3D point on the k-th face covering pixel (i,j) in the z-buffer.

We then decompose the input image I_{in} into K images I^k_{in}, where $I^k_{in}(i,j) = I_{in} \cdot p^k_{i,j}$, and splat the RGB pixel intensities from each I^k_{in} to a texture map layer $\hat{T}^k$ as

$$\hat{T}^k = \text{splat}(I^k_{in}, f^k) \tag{5}$$

where the flow $(u,v) = f^k(i,j)$ maps image coordinates (i,j) to UV coordinates (u,v) on the k-th mesh face in the z-buffer. Here splat is a differentiable splatting operation (based on [28]; see supplemental for details) from the image space I^k_{in} to the texture space $\hat{T}^k$. Finally, we sum all the K texture maps as the final UV texture map $\hat{T} = \sum_k \hat{T}^k$.



(a) input view 2D image I_{in} (b) mesh output target view I_{out} (c) inpainting on target view I_{paint} (d) ground-truth target view I_{tgt}

Figure 3: Parts of the target view (the gray area in b) are often invisible from the input and must be imagined based on prior knowledge. We make plausible predictions over the invisible regions with an inpaint network (c). However, this task is inherently uncertain (*e.g.* one cannot be sure about the rightmost cabinet in d).

In summary, the image pixels are splatted onto the texture space through each face, and blended together to obtain the final texture map. The entire process is differentiable with respect to both I_{in} and the mesh vertex coordinates $\{V\}$, as one can analytically compute $\partial\hat{T}^k/\partial I^k_{in}$, $\partial\hat{T}^k/\partial f^k$, $\partial f^k/\partial V$, $\partial D/\partial V$, and $\partial Z/\partial V$.

3.3. Learning scene geometry by view synthesis

To synthesize a novel view, we project the mesh vertex coordinates $\{V\}$ from the input camera pose θ_{in} to $\{V^{tgt}\}$ in the camera coordinate space of the target view-point θ_{tgt}. Then, we render the mesh $M^{tgt} = (\{V^{tgt}\}, \{F\})$ in the target camera pose along with its texture map $\hat{T}$ to output a 2D image I_{out} of size $W_{im} \times H_{im}$ as the target view:

$$I_{out} = \text{render\_mesh}(\{V^{tgt}\}, \{F\}, \hat{T}). \tag{6}$$

We use the differentiable mesh renderer in [31] so that we can compute the gradients $\partial I_{out}/\partial V^{tgt}$ and $\partial I_{out}/\partial\hat{T}$. Through mesh rendering, we also obtain a foreground mask F_{out} with the same size as I_{out}, indicating which pixels in the rendered image I_{out} are covered by the mesh and which pixels are from background color, as shown in Figure 3 (b).

Our model is supervised with paired input and target views of a scene (along with their camera poses). We use a pixel L1 loss $L^{rgb}_{out} = \|I_{out} - I_{tgt}\|_1 / (W_{im} \cdot H_{im})$ and a perceptual loss [46, 47] $L^{pc}_{out} = P(I_{out}, I_{tgt})$, where I_{tgt} is the ground-truth target view image. The model then needs just a single image at test time.

3.4. Inpainting and image refinement

The target view image consists of two parts: things that can be directly seen from the input view I_{in}, and things that need to be imagined based on our prior knowledge of the visual world, as illustrated in Figure 3. As our mesh warping and rendering procedure in Sec. 3.1, 3.2 and 3.3 builds a pixel-to-pixel correspondence between the input and the target view, it only renders pixels that are *visible* from the input view. To obtain a plausible imagination of the *invisible* image regions, we apply an inpainting network G on the

#	Method	Matterport [3] PSNR ↑ Both	PSNR ↑ InVis	PSNR ↑ Vis	SSIM ↑ Both	SSIM ↑ InVis	SSIM ↑ Vis	Perc Sim ↓ Both	Perc Sim ↓ InVis	Perc Sim ↓ Vis	Replica [41] PSNR ↑	SSIM ↑	Perc Sim ↓
1	Im2Im [53]	15.87	16.20	15.97	0.53	0.60	0.48	2.99	0.58	2.05	17.42	0.66	2.29
2	Tatarchenko *et al.* [42]	14.79	14.83	15.05	0.57	0.62	0.53	3.73	0.74	2.50	14.36	0.68	3.36
3	Vox [38] w/ UNet	18.52	17.85	19.05	0.57	0.57	0.57	2.98	0.77	1.96	18.69	0.71	2.68
4	Vox [38] w/ ResNet	20.62	19.64	21.22	0.70	0.69	0.68	1.97	0.47	1.19	19.77	0.75	2.24
5	SynSin [47]	20.91	19.80	21.62	0.71	0.71	0.70	1.68	0.43	0.99	21.94	0.81	1.55
6	ours w/o inpainting	–	–	25.42	–	–	0.80	–	–	0.68	–	–	–
7	ours	**24.67**	**22.90**	**26.00**	**0.82**	**0.77**	**0.82**	**1.05**	**0.35**	**0.54**	**23.51**	**0.85**	**1.32**

Table 1: Novel View Synthesis: Performance of our and previous approaches on the Matterport dataset and the Replica dataset. All models are trained on Matterport and evaluated on both datasets. See Sec. 4.1 for details.

rendered mesh I_{out} to fill the missing regions and output a new image $I_{paint} = G(I_{out})$ as the final target view.

We build our inpainting network based on the generator in pix2pixHD [46], which translates a 4-channel input (the rendered mesh I_{out} and its foreground mask F_{out}) into a 3-channel output image I_{paint}. Our inpainting network outputs an entire image – it not only fills the invisible regions but also refines the image details in the visible regions. We apply the same RGB pixel L1 loss L^{rgb}_{paint} and perceptual loss L^{pc}_{paint} as in Sec. 3.3 on the inpainting output I_{paint}.

3.5. Training

During training, we train our model using the Adam optimizer [15] with a weighted combination each loss as $L = \lambda_1 L^{rgb}_{out} + \lambda_2 L^{pc}_{out} + \lambda_3 L^{rgb}_{paint} + \lambda_4 L^{pc}_{paint} + \lambda_5 L_g + \lambda_6 L_m$ with $\lambda_1 = \lambda_3 = 8$, $\lambda_2 = \lambda_4 = 2$, $\lambda_5 = 0.2$, and $\lambda_6 = 10^{-4}$. Our model is trained for a total of 50000 iterations with batch size 64 and 10^{-4} learning rate.

We use a grid mesh with size $W_m \times H_m = 33 \times 33$ (and also 65×65 in Sec. 4.2). Following SynSin [47], we use $W_{im} \times H_{im} = 256 \times 256$ as the input and output image size. Our mesh implementation is based on PyTorch3D [31].

4. Experiments

We evaluate our model on three datasets: Matterport [3], Replica [41], and RealEstate10K [52], following the prior work's [47] experimental setup and details. In addition, we analyze the advantanges and limitations of wrapping a mesh sheet by testing on in-the-wild high resolution images.

4.1. Evaluation on Matterport and Replica

We first train and evaluate our approach on the Matterport [3] dataset, which contains 3D scans of homes. We load the Matterport dataset in the Habitat simulator [33], following the same training, validation, and test splits as in SynSin [47]. During training, we supervise our model with paired 2D images of the input and the target views. We empirically find that it works slightly better to first train the scene mesh predictor (Sec. 3.1) and then freeze the scene mesh to further train the inpainting network (Sec. 3.4), rather than training both components jointly from scratch.

Metrics. Following SynSin [47], we evaluate the quality of our predicted novel view images I_{paint} using three metrics: Peak Signal-to-Noise Ratio (**PSNR**; higher is better), Structural Similarity (**SSIM**; higher is better), and Perceptual Similarity distance (**Perc Sim**; lower is better). The Perc Sim metric is based on the convolutional feature distance between the prediction and the ground-truth, which is shown highly correlated with human judgement [51, 47]. Since only a part of the target view image can be seen from the input image as illustrated in Figure 3, we separately evaluate these metrics on visible regions (**Vis**, which can be seen from the input view), invisible regions (**InVis**, which cannot be seen but must be imagined), and the entire image (**Both**). Note that the visible region masks are obtained from the ground-truth scene geometry and camera frustum (available from the Habitat simulator) instead of predicted by our mesh, and are the same as in SynSin's evaluation.

Baselines. we compare our method to several previous approaches: **Im2Im** [53] is an image-to-image translation method which predicts a appearance flow to warp an input view to the target view based on an input camera transformation. **Tatarchenko *et al.*** [42] is similar to Im2Im, but directly predicts the target view image instead of an appearance flow. **Vox w/ UNet** and **Vox w/ ResNet** are two variants of the deep voxel representation [38] with different encoder-decoder architectures based on UNet or ResNet, implemented in [47]. **SynSin** [47] projects a dense feature point cloud (extracted from every image pixel) to the target camera pose and applies a refinement network on the point cloud projection to output the target view image. See Sec. 2 for more discussions on SynSin.

We also evaluate the prediction of our model before inpainting (*i.e.* directly using the mesh rendering output I_{out} as the target view) to analyze how well our method performs with texture sampling and mesh rendering alone.

Results. The results are shown in Table 1. Even without inpainting, the mesh rendering output I_{out} from our method already outperforms previous approaches by a large mar-

Figure 4: Novel views from our and previous methods on the Matterport dataset (scene mesh shown in the last column). The first row have same view-point change as in [47] while the second row has 2× larger camera angle change.

		Matterport [3] (2× cam. change)									Replica [41] (2× cam. change)		
		PSNR ↑			SSIM ↑			Perc Sim ↓			PSNR ↑	SSIM ↑	Perc Sim ↓
#	Method	Both	InVis	Vis	Both	InVis	Vis	Both	InVis	Vis			
1	Im2Im [53]	14.93	15.16	15.28	0.51	0.56	0.46	3.26	0.93	1.91	15.91	0.63	2.63
2	Tatarchenko *et al.* [42]	14.71	14.77	15.08	0.56	0.61	0.52	3.74	1.04	2.14	14.19	0.68	3.37
3	SynSin [47]	19.15	17.76	20.69	0.67	0.66	0.66	2.06	0.78	0.96	19.63	0.77	1.94
4	ours w/o inpainting	–	–	24.20	–	–	0.76	–	–	0.69	–	–	–
5	ours	**22.62**	**20.89**	**24.76**	**0.77**	**0.72**	**0.77**	**1.41**	**0.63**	**0.56**	**21.12**	**0.81**	**1.70**

Table 2: Novel View Synthesis: Generalization performance of our and previous approaches to larger view-point changes on the Matterport dataset and the Replica dataset. All models are trained on the Matterport dataset and evaluated on both datasets with 2× camera angle changes than in the training data. See Sec. 4.1 for details.

Figure 5: Generalization of our model (trained on Matterport) to the Replica dataset without retraining.

gin under all the three metrics on the visible regions. With the help of an inpainting network, our final output I_{paint} has significantly higher performance than previous work on both invisible and visible regions, achieving a new state-of-the-art performance on this dataset. Figure 4 shows view synthesis examples from our method and previous work on the Matterport dataset, where our method can paint things such as doorframe or sofa at more precise locations.

Generalization to the Replica dataset. Following [47], we also evaluate how well our model generalizes to another scene dataset, Replica [41], which contains high-quality laser scans of both homes and offices. We take our model trained on the Matterport dataset and directly evaluate on the Replica dataset without re-training. The results are shown in Table 1, where all methods are trained and evaluated under the same setting. It can be seen that our method achieves noticeably better generalization to this dataset and outperforms previous approaches by a large margin. Figure 5 shows view synthesis examples on the Replica dataset.

Generalization to larger view-point changes. We further analyze how well our and previous approaches generalize to larger camera pose changes beyond their training data. In this analysis, we sample new input-target view pairs on the test scenes with 2× larger camera angle changes than in the training data, and directly evaluate all approaches on these new view-points without retraining. The results are shown in Table 2, where our method largely outperforms other approaches under all metrics. Figure 4 (second row) shows an example under 2× larger camera angle change.

4.2. Evaluation on RealEstate10K

The RealEstate10K dataset [52] is built upon video frames extracted from YouTube videos on houses. The input view and the target view are different frames sampled from the video within a time range, and the camera poses are estimated using Structure-from-Motion over the video.

On this dataset, we follow the experimental setup in

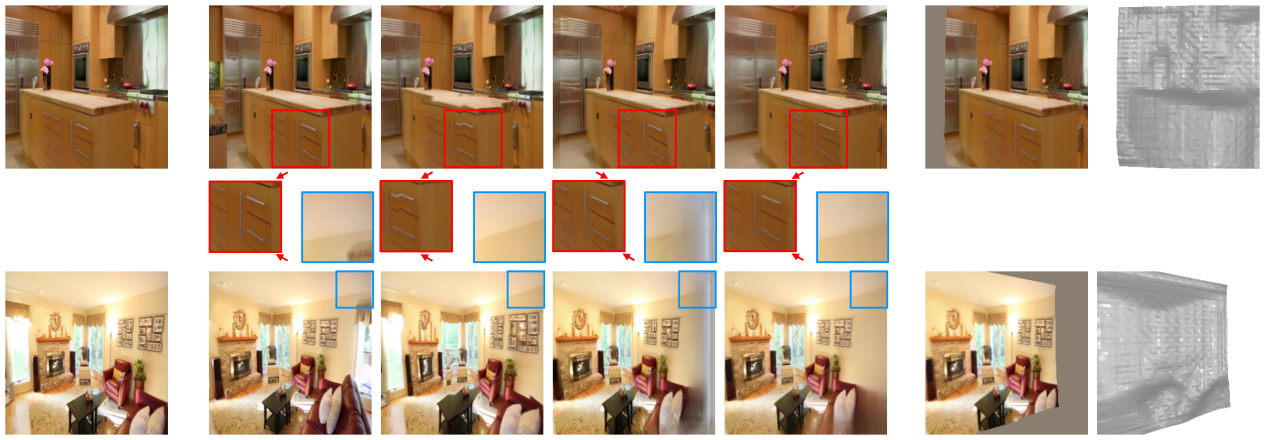


Figure 6: Novel views from our and previous methods on the RealEstate10K dataset (scene mesh shown in the last column).

	RealEstate10K [52]			
#	Method	PSNR ↑	SSIM ↑	Perc Sim ↓
1	Im2Im [53]	17.05	0.56	2.19
2	Tatarchenko *et al.* [42]	11.35	0.33	3.95
3	Vox [38] w/ UNet	17.31	0.53	2.30
4	Vox [38] w/ ResNet	21.88	0.71	1.30
5	3DView (similar to [26])	21.88	0.66	1.52
6	SynSin [47]	22.31	0.74	1.18
7	SynSin† [47]	22.83	0.75	1.13
8	StereoMag‡ [52]	25.34	**0.82**	1.19
9	ours (33×33 mesh)	26.24	**0.82**	0.83
10	ours (65×65 mesh)	**26.74**	**0.82**	**0.80**

Table 3: Results on the RealEstate10K dataset. We follow the evaluation protocol in SynSin and take the best metrics from predictions over two input views for the same target view. See Sec. 4.2 for details. (†: SynSin trained $5\times$ longer for 250k iterations; ‡: unlike all other approaches, StereoMag takes two views as input to predict the target view.)

SynSin [47] and use the same training, validation, and test data. In addition to using a 33×33 mesh, we also train our model with a higher resolution $W_m \times H_m = 65 \times 65$ mesh, which is initialized from a trained 33×33-mesh model with a new transposed convolution layer to upsample on the feature map $\{q_{w,h}\}$ in Sec. 3.1 to 65×65 spatial dimensions.

We compare our method to several previous approaches. In addition to the baselines in Sec. 4.1, we also compared to two additional approaches. **3DView** is a system similar to the Facebook 3D Photo [26] based on layered depth images, implemented in [47]. **StereoMag** [52] builds multi-plane images (MPIs) from a stereo pair, using images from *two* different views as input at test time. Except for StereoMag, all other methods use a single view at test time.

Results. We follow the evaluation protocol of [47] on RealEstate10K. However, to compare with StereoMag [52] that uses two input views on this dataset, the best metrics of two views were reported for single-view methods in [47]. That is, make two separate predictions based on two different input views respectively for each target view at test time and the select the best metrics among the two predictions as the scores for this target view. We believe this metric does not fully capture the true performance of single-image view synthesis as it evaluates on two views at test time, but we report it for apples-to-apples comparison to baselines. Note that apart from Table 3, all other results (Table 1, 2, 4) are average single-view results. The results in Table 3 show that our method achieves the highest performance under the evaluation protocol described above, outperforming previous approaches by a noticeable margin. Besides, a higher resolution 65×65 mesh gives a further performance boost.

Detailed analyses. As discussed above, we further evaluate by our usual protocol of taking the average metrics over all predictions (which is used on Matterport and Replica in Sec. 4.1), to measure how well the model does on average from a single input view. Apart from metrics over the entire image, we would also like to analyze how well each model does on rendering regions seen in the input view vs. invisible regions (where things must be imagined). However, we cannot compute the exact visibility map as there are no ground-truth geometry annotations on the RealEstate10K dataset. To get an approximation, we evaluate on the central $\frac{W_{im}}{2} \times \frac{H_{im}}{2} = 128 \times 128$ crop of the target image (**Center**, which is nearly always visible) and the rest of the image (**Peripheral**, containing most of the invisible regions).

These detailed comparisons are shown in Table 4. It can be seen that our method achieves the highest performance on both the center regions (which are mostly visible) and the peripheral regions, outperforms the previous single-view based approaches by a large margin. Figure 6 shows predicted novel views on this dataset. In addition, we visualize the pixel-wise squared error map on the prediction from our method and SynSin [47] in Figure 7, where our method paints objects at more precise locations compared to SynSin, resulting in higher PSNR and better quality.

#	Method	RealEstate10K [52] (averaged metrics over all predictions)								
		PSNR ↑			SSIM ↑			Perc Sim ↓		
		Both	Peripheral	Center	Both	Peripheral	Center	Both	Peripheral	Center
1	Im2Im [53]	15.56	15.65	15.80	0.51	0.53	0.44	2.59	1.93	0.65
2	Tatarchenko *et al*. [42]	11.11	11.32	10.68	0.32	0.35	0.24	3.96	2.96	1.13
3	SynSin [47]	20.11	20.02	21.15	0.67	0.67	0.67	1.52	1.18	0.31
4	SynSin† [47]	20.47	20.35	21.65	0.68	0.68	0.68	1.49	1.16	0.29
5	ours (33 × 33 mesh)	23.11	22.90	24.83	**0.75**	0.74	**0.76**	1.17	0.94	**0.21**
6	ours (65 × 65 mesh)	**23.41**	**23.20**	**25.17**	**0.75**	**0.75**	**0.76**	**1.14**	**0.92**	**0.21**

Table 4: Performance of our and previous approaches on RealEstate10K, with metrics averaged over all predictions. We evaluate on the entire 256×256 image (**both**), the **center** 128×128 crop (nearly always visible), and the remaining **peripheral** regions (containing most of the invisible regions). See Sec. 4.2 for details. (†: SynSin trained 5× longer for 250k iterations.)

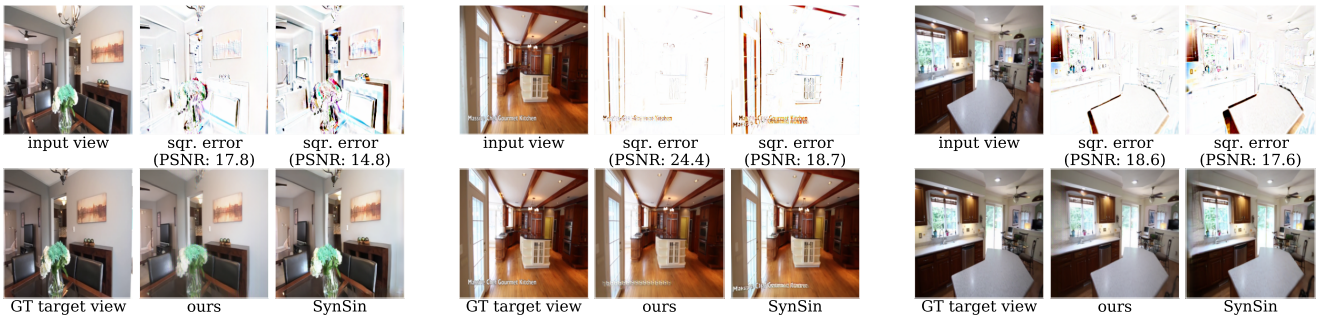


Figure 7: Squared error maps in target view from our method and SynSin [47] on the RealEstate10K dataset (darker is higher error). Our method paints things in the novel view at more precise locations, resulting in lower error and higher PSNR.

4.3. Analysis: testing the limits of wrapping sheets

So far, we showed that the idea of wrapping a mesh sheet onto an image achieves strong performance across all benchmarks. But one might wonder how good is a planar sheet prior for novel view synthesis in any arbitrary images. To test the limits of wrapping a mesh *sheet*, we test it over a large variety of images including outdoor scenes, outdoor objects, indoor scenes, indoor objects, and even artistic paintings. We analyze our underlying mesh data structure by pretraining depth [19] to fill in the z values, and examine how well it generates novel views in-the-wild. As shown in Figure 1 (top row), although missing a few details (such as tree branches), a scene mesh sheet captures the geometric structures sufficient enough to render high-resolution (960×960) photorealistic novel views even from very large viewpoint changes. Please see videos at `worldsheet.github.io` for animation of continuously generated views. This result confirms that our mesh sheet data structure and warping procedure, despite being simple, are flexible enough to handle the variety of the visual world.

Limitations and Future Work. Although shrink-wrapping a mesh sheet onto images works well on a wide range of scenes, one limitation is that we currently do not cut the mesh on depth discontinuities, assuming that the foreground objects (*e.g.* trees) are connected to the background (*e.g.* sky), which can create artifacts near object boundaries. Figure 8 shows failure cases due to depth discontinuity.

Figure 8: Some failures of our approach due to depth discontinuity, where the foreground objects (trees or flower) are blurry at their boundaries. See Sec. 4.3 for a discussion.

5. Conclusion

In this work, we propose Worldsheet, which synthesizes novel views from a single image by shrink-wrapping the scene in a grid mesh. Our approach jointly learns the scene geometry and generates novel views through differentiable texture sampling and mesh rendering, supervised with only 2D images of the input and the target views. The approach is category-agnostic and end-to-end trainable resulting in state-of-the-art performance on single-image view synthesis across three datasets by a large margin. Furthermore, we show that our approach to wrap a sheet is flexible enough to handle the variety of the visual world.

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Worldsheet: Wrapping the World in a 3D Sheet for View Synthesis from a Single Image
(Supplementary Material)

A. Continuous and large viewpoint changes

Our approach allows synthesizing continuous novel views by smoothly moving to a new camera pose largely different from the input. We kindly request the readers to check out the videos at https://worldsheet.github.io for a better understanding of the performance of our method in an absolute sense and in comparison to other approaches.

In these videos, we compare our synthesized novel views (from a single image) to SynSin [47] on the RealEstate10K dataset with simulated large view-point changes (the first frame contains the input view and the rest of the frames are synthesized). From the videos, it can be seen that our model can generate novel views with much larger camera translation and rotation than in the training data, while SynSin often suffers from severe artifacts in these cases, likely because its refinement network does not generalize well to a sparser point cloud (resulting from large camera zoom-in or rotation).

We also show in these videos continuously synthesized novel views on high resolution (960×960) images over a wide range of scenes (the first frame is the input view), as described in our analysis in Sec. 4.3 in the main paper.

B. Details on differentiable texture sampler

Our differentiable texture sampler (Sec. 3.2 in the main paper) splat image pixels onto the texture space through each face. This splatting procedure involves three main steps: forward-mapping, normalization, and hole filling.

Suppose the flow $(u, v) = f(i, j)$ maps image coordinates (i, j) to UV coordinates (u, v) on the texture map, which can be obtained through mesh rasterization (here we drop the face index k for simplicity). To implement $\hat{T} = \text{splat}(I_{in}, f)$ (Eqn. 5 in the main paper), we first forward-map the image pixels to the texture map, using bilinear assignment when the mapped texture coordinates (u, v) do not fall on integers, as forward_map below.

```
function T = forward_map(I, f)
  T = all_zeros(W_uv, H_uv)
  for i in 1:W_im
    for j in 1:H_im
      u, v = f(i, j)
      uf, uc = floor(u), ceil(u)
      vf, vc = floor(v), ceil(v)
      T[uf,vf] += I[i,j] * (uc - u) * (vc - v)
      T[uc,vf] += I[i,j] * (u - uf) * (vc - v)
      T[uf,vc] += I[i,j] * (uc - u) * (v - vf)
      T[uc,vc] += I[i,j] * (u - uf) * (v - vf)
    end
  end
  return T
```

Gradients can be taken over f through the bilinear weights. Our implementation is based on the sum splatting in [28].

However, forward mapping alone will lead to incorrect pixel intensity (*e.g.* imagine down-scaling an image to half its width and height by forward-mapping – each pixel in the low-resolution image will receive assignment from 4 pixels and become $4\times$ brighter). Hence, a second normalization step is applied:

$$\hat{T}_{sum} = \text{forward\_map}(I_{in}, f) \quad \text{(B.1)}$$

$$\hat{W}_{sum} = \text{forward\_map}(I_{one}, f) \quad \text{(B.2)}$$

$$\hat{T}_{norm} = \hat{T}_{sum} / \max\left(\hat{W}_{sum}, 10^{-4}\right) \quad \text{(B.3)}$$

where I_{one} is an $W_{im} \times H_{im}$ image with all ones as its pixel intensity. $\hat{T}_{norm}$ contains the normalized splatting result. A threshold 10^{-4} is applied to avoid division by zero (which could happen due to holes described below).

Filling holes with Gaussian filtering. It is well known that the bilinear forward mapping above often leads to holes in the output (*e.g.* imagine up-scaling an image to a much larger size – there will be gaps in the output image as some pixels will not receive assignments). To minimize hole occurrence, in our UV texture map we assigned the UV coordinates of each mesh vertex with an equally-spaced $W_m \times H_m$ lattice grid, and use the same image size as the texture map size ($W_{uv} \times H_{uv} = W_{im} \times H_{im}$). This ensures that most texels on the texture map receive assignments in forward mapping, so that holes rarely occur in $\hat{T}_{norm}$. However, to address corner cases, we further apply a Gaussian filter to fill the holes on $\hat{T}_{norm}$ (where $\hat{W}_{sum}$ is zero as no assignment is received from forward-mapping):

$$\hat{M} = \text{I}\left[\hat{W}_{sum} > 0\right] \quad \text{(B.4)}$$

$$\hat{T}_g = \left(F_g * \hat{T}_{norm}\right) / \left(F_g * \hat{M}\right) \quad \text{(B.5)}$$

$$\hat{T} = \hat{M} \cdot \hat{T}_{norm} + \left(\left(1 - \hat{M}\right) \cdot \hat{T}_g\right) \quad \text{(B.6)}$$

where F_g is a discrete 2D Gaussian kernel for image filtering (we use kernel size 7 and standard deviation 2 for

#	Method	Matterport [3] PSNR ↑ Both	InVis	Vis	SSIM ↑ Both	InVis	Vis	Perc Sim ↓ Both	InVis	Vis	Replica [41] PSNR ↑	SSIM ↑	Perc Sim ↓
1	Im2Im [53]	15.87	16.20	15.97	0.53	0.60	0.48	2.99	0.58	2.05	17.42	0.66	2.29
2	Tatarchenko *et al*. [42]	14.79	14.83	15.05	0.57	0.62	0.53	3.73	0.74	2.50	14.36	0.68	3.36
3	Vox [38] w/ UNet	18.52	17.85	19.05	0.57	0.57	0.57	2.98	0.77	1.96	18.69	0.71	2.68
4	Vox [38] w/ ResNet	20.62	19.64	21.22	0.70	0.69	0.68	1.97	0.47	1.19	19.77	0.75	2.24
5	SynSin [47]	20.91	19.80	21.62	0.71	0.71	0.70	1.68	0.43	0.99	21.94	0.81	1.55
6	SynSin (w/ depth sup.) [47]	21.59	20.32	22.46	0.72	0.71	0.71	1.60	0.43	0.92	22.54	0.80	1.55
7	ours	**24.67**	**22.90**	**26.00**	**0.82**	**0.77**	**0.82**	**1.05**	**0.35**	**0.54**	**23.51**	**0.85**	**1.32**
8	ours (w/ depth sup.)	24.75	22.85	26.18	0.82	0.77	0.82	1.06	0.36	0.54	22.78	0.84	1.51

Table C.1: Analyses of our model and SynSin using explicit depth supervision during training (line 8 and 6) on the Matterport dataset. Our model without depth (the default setting; line 7) performs nearly equally well as its counter part with depth supervision (line 8) on Matterport and generalizes better to Replica, outperforming both variants of SynSin (line 5 and 6).

F_g in our implementation). Here $\hat{M}$ is a binary mask indicating which pixels have received assignments in forward mapping (*i.e*. 1 means valid and 0 means holes), $\hat{T}_g$ is the Gaussian-blurred version of $\hat{T}_{norm}$ (where the division ensures the correct pixel intensity; otherwise it will be darker due to holes in $\hat{T}_{norm}$) and is used to fill only the holes in $\hat{T}_{norm}$. We use $\hat{T}$ in Eqn. B.6 as the final splatting output.

C. Ablation study: using depth supervision

In our experiments in the paper, we show that our model can be trained using only two views of a scene *without* 3D or depth supervision. In this section, we further analyze our approach by training it *with* depth supervision on the Matterport dataset, where the ground-truth depth can be obtained from the Habitat simulator.

In this analysis, we modify the differentiable mesh renderer to render RGB-D images from our mesh, and apply an L1 loss between the ground-truth and the rendered depth as additional supervision. We also compare to the performance of SynSin with depth supervision (reported in [47]). The results are shown in Table C.1. It can be seen that our model without depth supervision (the default setting; line 7) works almost equally as well as its counterpart using depth supervision (line 8) on the Matterport dataset and generalizes better to the Replica dataset. In addition, it outperforms SynSin under both supervision settings (line 5 and 6).

D. Hyper-parameters in our model

In our nonlinear function $g(\cdot)$ to scale the network prediction into depth values (in Eqn. 3 in the main paper), we use different output scales based on the depth range in each dataset. On Matterport and Replica, we use

$$g(\psi) = 1/(0.75 \cdot \sigma(\psi) + 0.01) - 1. \quad \text{(D.1)}$$

On RealEstate10K (which has larger depth range), we double the output depth scale and use

$$g(\psi) = 2/(0.75 \cdot \sigma(\psi) + 0.01) - 2. \quad \text{(D.2)}$$

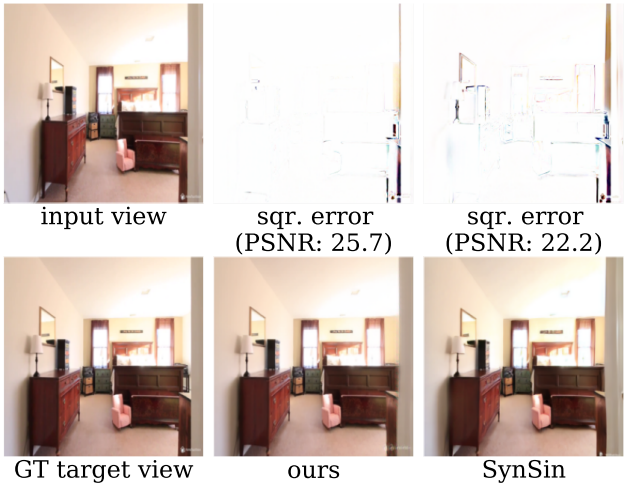
However, we find that the performance of our model is quite insensitive to the hyper-parameters in $g(\cdot)$.

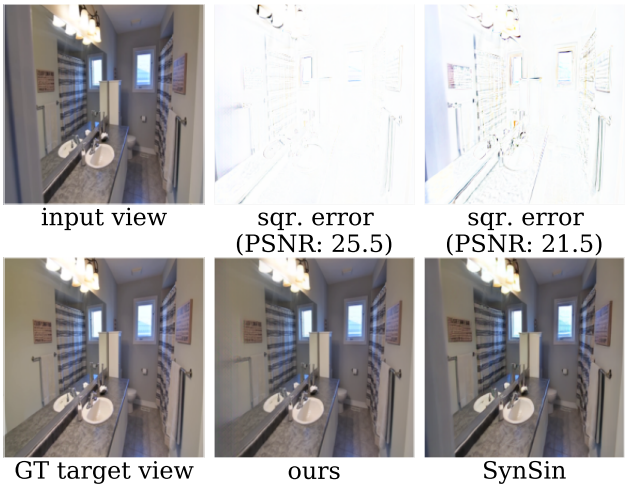
In our differentiable texture sampler and the mesh renderer, we mostly follow the hyper-parameters in PyTorch3D. We use $K = 10$ faces per pixel and 1e-8 blur radius in mesh rasterization, 1e-4 sigma and 1e-4 gamma in softmax RGB blending, and background color filled with the mean RGB intensity on each dataset. On Matterport and Replica, the input views have 90-degree field-of-view. On RealEstate10K, we multiply the actual camera intrinsic matrix of each frame into its camera extrinsic R and T matrices, so that we can still use the same intrinsics and 90-degree field-of-view in the renderer. On high resolution images in the wild (Sec. 4.3 in the main paper), we assume 45-degree field-of-view.

We choose our mesh size W_m and H_m based on the image size. In our experiments on Matterport and Replica (Sec. 4.1 in the main paper), we use 256×256 input image resolution following SynSin [47], and use pixel stride 8 on the lattice grid sheet (from which our mesh is built), resulting in $W_m = H_m = 1 + 256/8 = 33$. On the RealEstate10K dataset (Sec. 4.2 in the main paper), we additionally experiment with pixel stride 4 on the grid sheet, giving $W_m = H_m = 1 + 256/4 = 65$. In our analysis on high resolution images in the wild (resized to have the image long side equal to 960 and padded to 960×960 square size for ease of rendering in PyTorch3D; Sec. 4.3 in the main paper), we use $W_m \times H_m = 129 \times 129$ mesh on the actual image regions (not including the padding regions).

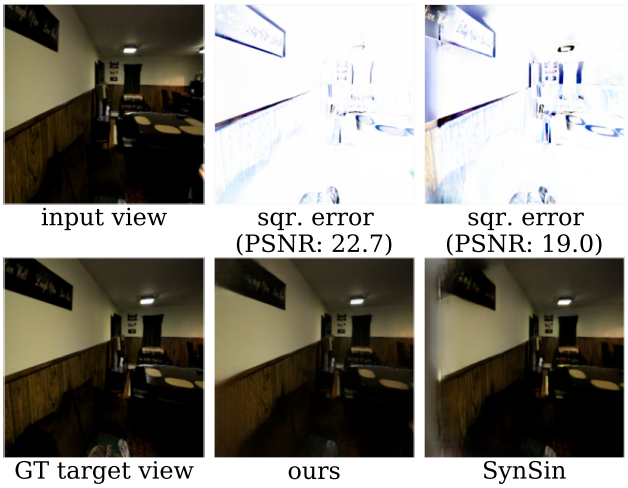
E. More visualized examples

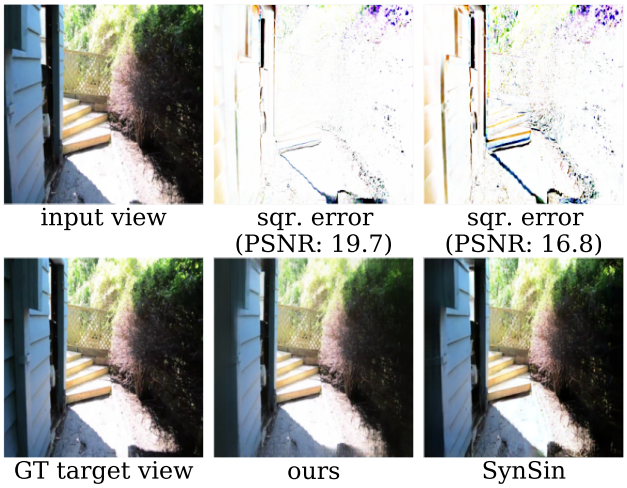
Figure E.1 shows additional visualization and error map comparisons between our approach and SynSin on the RealEstate10K dataset, where our method paints things in the novel view at more precise locations with lower error and higher PSNR.


input view
sqr. error (PSNR: 25.7)
sqr. error (PSNR: 22.2)
GT target view
ours
SynSin


input view
sqr. error (PSNR: 25.5)
sqr. error (PSNR: 21.5)
GT target view
ours
SynSin


input view
sqr. error (PSNR: 24.5)
sqr. error (PSNR: 22.8)
GT target view
ours
SynSin


input view
sqr. error (PSNR: 22.7)
sqr. error (PSNR: 19.0)
GT target view
ours
SynSin


input view
sqr. error (PSNR: 19.7)
sqr. error (PSNR: 16.8)
GT target view
ours
SynSin

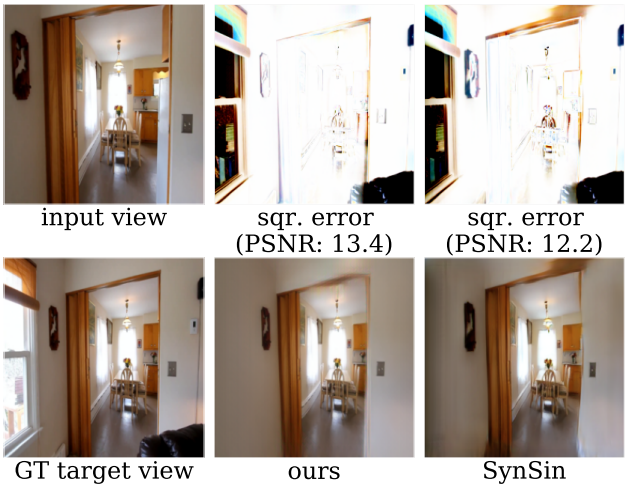

input view
sqr. error (PSNR: 13.4)
sqr. error (PSNR: 12.2)
GT target view
ours
SynSin

Figure E.1: Additional synthesized novel views (with squared error maps of the target view) from our method and SynSin [47] on the RealEstate10K dataset (darker is higher error). Our method paints things in the novel view at more precise locations, resulting in lower error and higher PSNR.