Text2Room: Extracting Textured 3D Meshes from 2D Text-to-Image Models

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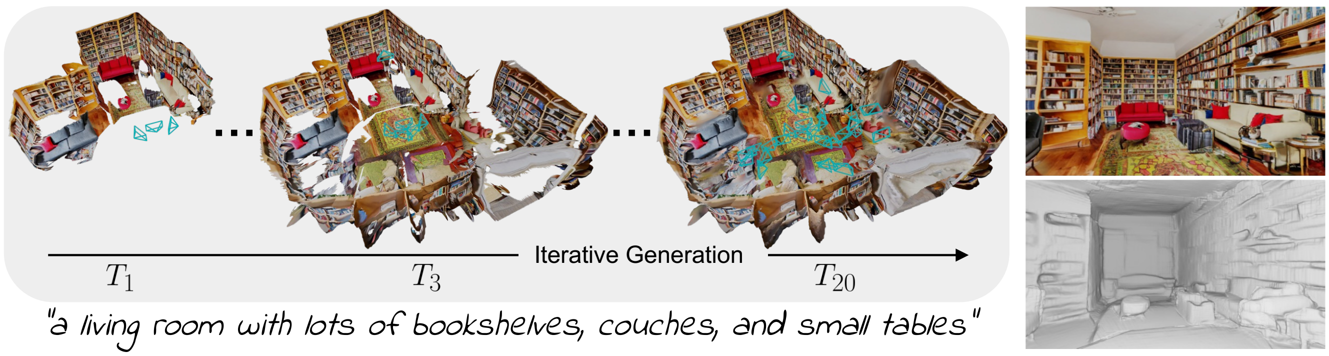

(a) 3D Mesh Generation from Text (b) Rendered Image + Mesh

Figure 1. **Textured 3D mesh generation from text prompts.** We generate textured 3D meshes from a given text prompt using 2D text-to-image models. (a) The scene is iteratively created from different viewpoints (marked in blue). (b) Our generated mesh contains compelling textures and geometry. We remove the ceiling in the top-down views for better visualization of the scene layout.

Abstract

We present Text2Room[1], a method for generating room-scale textured 3D meshes from a given text prompt as input. To this end, we leverage pre-trained 2D text-to-image models to synthesize a sequence of images from different poses. In order to lift these outputs into a consistent 3D scene representation, we combine monocular depth estimation with a text-conditioned inpainting model. The core idea of our approach is a tailored viewpoint selection such that the content of each image can be fused into a seamless, textured 3D mesh. More specifically, we propose a continuous alignment strategy that iteratively fuses scene frames with the existing geometry to create a seamless mesh. Unlike existing works that focus on generating single objects [56, 41] or zoom-out trajectories [18] from text, our method generates complete 3D scenes with multiple objects and explicit 3D geometry. We evaluate our approach using qualitative and quantitative metrics, demonstrating it as the first method to generate room-scale 3D geometry with compelling textures from only text as input.

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[1]https://lukashoel.github.io/text-to-room

1. Introduction

Mesh representations of 3D scenes are a crucial component for many applications, from AR/VR asset creation to computer graphics, yet creating these 3D assets remains a painstaking process that requires considerable expertise. In the 2D domain, recent works have successfully created high-quality images from text using generative models, such as diffusion models [65, 58, 67]. These methods significantly reduce the barriers to creating images that contain a user's desired content, effectively helping towards the democratization of content creation. An emerging line of work has sought to apply similar methods to create 3D models from text [9, 56, 29, 41, 38], yet existing approaches come with a number of significant limitations and lack the generality of 2D text-to-image models.

One of the core challenges of generating 3D models is coping with the lack of available 3D training data, as 3D datasets are vastly smaller than those available in many other applications, such as 2D image synthesis. For example, methods that directly use 3D supervision, such as Chen *et al.* [9], are often limited to datasets of simple shapes, such as ShapeNet [8]. To address these data limitations, recent methods [56, 29, 41, 38, 88] lift the expressive power of 2D text-to-image models into 3D by formulating 3D generation as an iterative optimization problem in the image domain. This allows them to generate 3D objects stored in a radiance field representation, demonstrating the ability to generate arbitrary (neural) shapes from text. However, these methods cannot easily be extended to create room-scale 3D structure and texture. The challenge of generating large scenes is ensuring that the generated output is dense and coherent across outward-facing viewpoints, and that these views contain all of the required structures, such as walls, floors, and furniture. Additionally, a mesh remains a desired representation for many end-user tasks, such as rendering on commodity hardware (which requires an additional conversion step as presented in Lin *et al.* [41]).

To address these shortcomings, we propose a method that extracts scene-scale 3D meshes from off-the-shelf 2D text-to-image models. Our method iteratively generates a scene through inpainting and monocular depth estimation. We produce an initial mesh by generating an image from text, and backproject it into 3D using a depth estimation model. Then, we iteratively render the mesh from novel viewpoints. From each one, we fill in holes in the rendered images via inpainting, then fuse the generated content into the mesh (Fig. 1a).

Our iterative generation scheme has two important design considerations: how we choose the viewpoints, and how we merge generated scene content with the existing mesh. We first select viewpoints from predefined trajectories that will cover large amounts of scene content, then adaptively select viewpoints that close remaining holes. When merging generated content with the mesh, we align the two depth maps to create smooth transitions, and remove parts of the mesh that contain distorted textures. Together, these decisions lead to large, scene-scale 3D meshes with compelling textures and consistent geometry (Fig. 1b), that can represent a wide range of rooms.

To summarize, our contributions are:

- Generating 3D meshes of room-scale indoor scenes with compelling textures and geometry from any text input.
- A method that leverages 2D text-to-image models and monocular depth estimation to lift frames into 3D in an iterative scene generation. Our proposed depth alignment and mesh fusion steps, enable us to create seamless and undistorted geometry and textures.
- A two-stage tailored viewpoint selection that samples camera poses from optimal positions to first create the room layout and furniture and then close any remaining holes, creating a watertight mesh.

2. Related Work

Text-based Generation has seen significant advances due to large-scale image-text datasets [73, 72, 14, 71] and scalable generative model architectures [16, 66, 60, 32], enabling synthesis of novel images from text [20, 3, 54].

Recently, diffusion models [78, 23, 80, 81, 82] achieved impressive results on image synthesis [15, 65, 67, 50, 58] through improvements like latent space denoising [65, 84], faster sampling [23, 79, 52, 34], and better guidance [24].

In particular, *text-to-image* methods like Stable Diffusion [65], Imagen [67], GLIDE [50] and DALL·E 2 [58] yield diverse, high-fidelity, and controllable [6, 94] outputs. Text-based generation has been extended to other modalities including audio [35, 17, 28, 70], video [75, 91, 85, 25], and 4D fields [76]. We use *text-to-image* models by lifting their generated output into complete 3D scene meshes.

Text-to-3D. Several methods use 3D data for supervised training of text-to-3D models [9, 51, 5]; however this direction remains challenging due to the lack of large-scale aligned datasets of text and 3D.

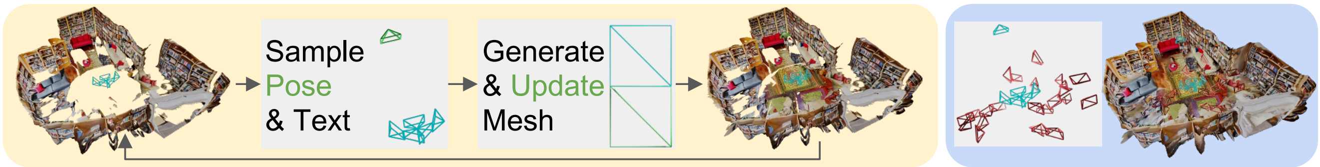
Alternative approaches use 2D vision-language models like CLIP [57] to create 3D content by formulating the generation as an optimization problem in the image domain [86, 29, 38, 48, 30] or as object alignment [69]. Related methods refine existing 3D input through text guidance in a similar fashion [46, 10, 87, 62].

Recent methods [56, 41, 45, 88, 44] combine large text-to-image diffusion models [65, 67] and neural radiance fields [47] to generate 3D objects without training. Other approaches train custom diffusion models on a similar text-to-3D task [39, 49, 12]. In contrast, we use a fixed text-to-image model and extract a 3D mesh representing entire scenes of many objects and structural elements like walls.

3D-Consistent View Synthesis from a Single Image. Several methods have been proposed that perform novel-view-synthesis from a single image [64, 90, 74, 61, 19]. Others optimize a neural 3D representation of an object, that can be viewed from arbitrary novel view points [92, 89, 1]. Another line of work performs *perpetual view generation* [77, 42, 40, 7], synthesizing videos via a *render-refine-repeat* pattern from a single RGB image that depict a scene along a forward-facing camera trajectory. In very recent concurrent work, Fridman *et al.* [18] create 3D scenes from text, but focus on this type of 3D-consistent "zoom-out" video generation. Instead, we generate complete, textured 3D room geometry from arbitrary trajectories.

3. Method

Our method creates a textured 3D mesh of a complete scene from text input. To this end, we continuously fuse generated frames from a 2D text-to-image model at different poses into a joint 3D mesh, creating the scene over time. The core idea of our approach is a two-stage tailored viewpoint selection, that first generates the scene layout and objects and then closes remaining holes in the 3D geometry (Section 3.4). We visualize this workflow in Figure 2. For each pose in both stages, we apply an iterative scene generation scheme to update the mesh (Section 3.1). We first align each frame with the existing geometry with a depth align-



(a) Scene Generation Stage

(b) Scene Completion Stage

Figure 2. **Method overview**. We iteratively create a textured 3D mesh in two stages. (a) First, we sample predefined poses and text to generate the complete scene layout and furniture. Each new pose (marked in green) adds newly generated geometry to the mesh (depicted by green triangles) in an iterative scene generation scheme (see Figure 3 for details). Blue poses/triangles denote viewpoints that created geometry in a previous iteration. (b) Second, we fill in the remaining unobserved regions by sampling additional poses (marked in red) after the scene layout is defined.

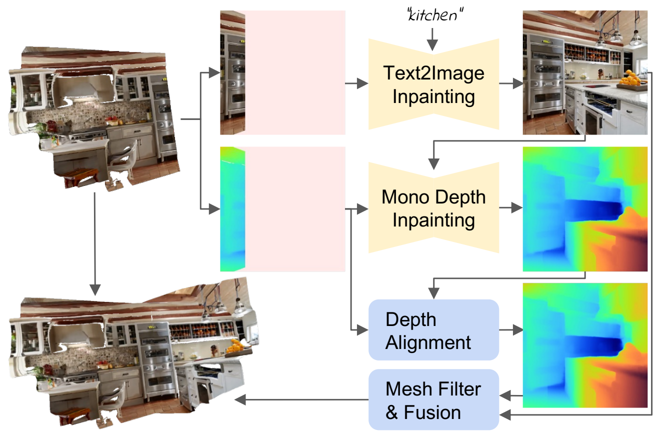


Figure 3. **Iterative scene generation**. For each new pose, we render the current mesh to obtain partial RGB and depth renderings. We complete both, utilizing respective inpainting models and the text prompt. Next, we perform depth alignment (see Section 3.2) and mesh filtering (see Section 3.3) to obtain an optimal next mesh patch, that is finally fused with the existing geometry.

ment strategy (Section 3.2). Next, we triangulate and filter the novel content to merge it into the mesh (Section 3.3).

3.1. Iterative 3D Scene Generation

Our scene is represented as a mesh $\mathcal{M} = (\mathcal{V}, \mathcal{C}, \mathcal{S})$ where the vertices $\mathcal{V} \in \mathbb{R}^{N\times 3}$, vertex colors $\mathcal{C} \in \mathbb{R}^{N\times 3}$ and the face set $\mathcal{S} \in \mathbb{N}_0^{M\times 3}$ are generated over time. Input to our method is a set of arbitrary text prompts $\{P_t\}_{t=1}^{T}$ that corresponds to our selected poses $\{E_t\}_{t=1}^{T} \in \mathbb{R}^{3\times 4}$ in both stages. Inspired by recent methods [42, 40], we iteratively build up the scene, following a *render-refine-repeat* pattern. We summarize this iterative scene generation process in Figure 3. Formally, for each step of generation t, we first render the current scene from a novel viewpoint:

$$I_t, d_t, m_t = r(\mathcal{M}_t, E_t), \tag{1}$$

where r is a classical rasterization function without shading, I_t is the rendered image, d_t the rendered depth and m_t the image-space mask, that marks pixels without observed content. We then use a fixed text-to-image model $\mathcal{F}_{t2i}$ to inpaint unobserved pixels according to the text prompt:

$$\hat{I}_t = \mathcal{F}_{t2i}(I_t, m_t, P_t). \tag{2}$$

Next, we inpaint unobserved depth by applying a monocular depth estimator $\mathcal{F}_d$ in our depth alignment (see Section 3.2):

$$\hat{d}_t = \textit{predict-and-align}(\mathcal{F}_d, I_t, d_t, m_t). \tag{3}$$

Finally, we combine the novel content $\{\hat{I}_t, \hat{d}_t, m_t\}$ with the existing mesh by our fusion scheme (see Section 3.3):

$$\mathcal{M}_{t+1} = \textit{fuse}(\mathcal{M}_t, \hat{I}_t, \hat{d}_t, m_t, E_t). \tag{4}$$

3.2. Depth Alignment Step

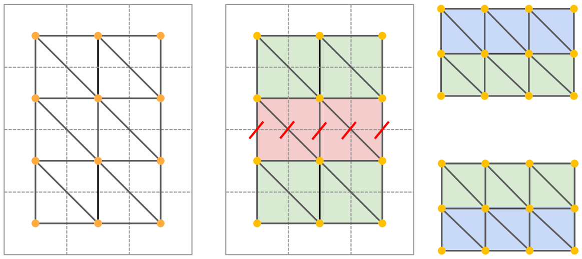
To lift a 2D image I into 3D, we predict the per-pixel depth. To correctly combine old and new content, it is necessary that both align with each other. In other words, similar regions in a scene like walls or furniture should be placed at similar depth. However, directly using the predicted depth for backprojection leads to hard cuts and discontinuities in the 3D geometry, since the depth is inconsistent in scale between subsequent viewpoints (see Figure 7a).

To this end, we perform depth alignment in two-stages. First, we use a state-of-the-art depth inpainting network [4] that takes ground-truth depth d for known parts in the image as input and aligns the prediction to it: $\hat{d}_p = \mathcal{F}_d(I, d)$.

Inspired by Liu *et al.* [42] we then improve the result by optimizing for scale and shift parameters $\gamma, \beta \in \mathbb{R}$, aligning predicted and rendered disparity in the least squares sense:

$$\min_{\gamma,\beta} \left\| m \odot \left(\frac{\gamma}{\hat{d}_p} + \beta - \frac{1}{d} \right) \right\|^2, \tag{5}$$

where we mask out unobserved pixels via m. We can then extract the aligned depth as $\hat{d} = (\frac{\gamma}{\hat{d}_p} + \beta)^{-1}$. Finally, we smooth $\hat{d}$ by applying a 5×5 Gaussian kernel at the mask edges (see supplemental material for more details).



(a) Pixel Triangulation (b) Face Filtering (c) Mesh Fusion

Figure 4. **Visualization of our mesh fusion step.** (a) We triangulate an image, such that 4 neighboring pixels (orange dots) create two faces. (b) We filter a face (marked in red), if its surface normal forms a small grazing angle with the viewing direction or if any edge in world space is too long. (c) We fuse the remaining faces (marked in green) with the existing geometry (marked in blue).

3.3. Mesh Fusion Step

At each step, we insert new content $\{\hat{I}_t, \hat{d}_t, m_t\}$ into the scene. For that, we first backproject the image-space pixels into a world-space point cloud:

$$\mathcal{P}_t = \{E_t^{-1} K^{-1} \cdot \hat{d}_t[u,v] \cdot (u,v,1)^T\}_{u=0,v=0}^{W,H}, \quad (6)$$

where $K \in \mathbb{R}^{3\times3}$ are the camera intrinsics and W, H are image width and height, respectively. We then use a simple triangulation scheme (Figure 4a), where each four neighboring pixels $\{(u,v),(u{+}1,v),(u,v{+}1),(u{+}1,v{+}1)\}$ in the image form two triangles. Since the estimated depth is noisy, this naïve triangulation creates stretched out 3D geometry (see Figure 7b). To alleviate this problem, we propose two filters that remove stretched out faces (Figure 4b).

First, we filter faces based on their edge length. We remove a face if the Euclidean distance of any face edge is larger than a threshold δ_{edge}. Second, we filter faces based on the angle between surface normal and viewing direction:

$$\mathcal{S} = \{(i_0, i_1, i_2) | n^T v > \delta_{sn}\} \quad (7)$$

where $\mathcal{S}$ is the face set, (i_0, i_1, i_2) are the vertex indices of the triangle, δ_{sn} is the threshold, $n \in \mathbb{R}^3$ is the normalized face normal, and $v \in \mathbb{R}^3$ is the normalized view direction in world space from the camera center towards the average pixel location from which the triangle originated. This avoids creating texture for large regions of the mesh from a comparatively small number of pixels from an image.

Finally, we fuse together the newly generated mesh patch and the existing geometry (Figure 4c). All faces that are backprojected from pixels falling into the inpainting mask m_t are stitched together with their neighboring faces, which are already part of the mesh. Precisely, we continue the triangulation scheme at all edges of m_t, but use the existing vertex positions of $\mathcal{M}_t$ to create the corresponding faces.

3.4. Two-Stage Viewpoint Selection

A key part of our method is the choice of text prompts and camera poses from which the scene is synthesized. Users can in principle choose these inputs arbitrarily to create any desired indoor scene. However, the generated scene can degenerate and contain stretch and hole artifacts, if poses are chosen carelessly (see Figure 7 and supplemental material). To this end, we propose a two-stage viewpoint selection strategy, that samples each next camera pose from optimal positions and refines empty regions subsequently.

Generation Stage. In the first stage, we create the main parts of the scene, including the general layout and furniture. We subsequently render *predefined* trajectories in different directions that eventually cover the whole room. We found generation works best, if each trajectory starts off from a viewpoint with mostly unobserved regions. This generates the outline of the next chunk, while still being connected to the rest of the scene (e.g., see Figure 3). Then, we complete the 3D structure of that chunk by moving and rotating into it subsequently until the end of the trajectory.

Additionally, we ensure an optimal observation distance for each pose. We translates camera positions $T_0{\in}\mathbb{R}^3$ along the look-at direction $L{\in}\mathbb{R}^3$ uniformly: $T_{i+1}{=}T_i{-}0.3L$. We stop if the mean rendered depth is larger than 0.1 or discard the camera after 10 steps. This avoids views too close to existing geometry. For example, the green pose in Figure 2a is moved back as far as possible into the existing geometry such that it views most of the empty floor region.

We create closed room layouts following this principle, by choosing trajectories that generate the next chunks in a circular motion, roughly centered around the origin. We found it helpful to discourage the text-to-image generator from generating furniture in unwanted regions by engineering the text prompts accordingly. For example, for poses looking at the floor or ceiling, we choose text prompts that only contain the words “floor” or “ceiling”, respectively.

Completion Stage. After the first stage, the scene layout and furniture is defined. However, it is impossible to choose sufficient poses *a-priori*. Since the scene is generated on-the-fly, the mesh contains holes that were not observed by any camera (see Figure 7c). We complete the scene by sampling additional poses *a-posteriori*, looking at those holes.

Inspired by trajectory optimization [22, 63], we voxelize the scene into dense uniform cells. We sample random poses in each cell, discarding those being too close to existing geometry. We select one pose per cell that views most unobserved pixels (e.g., see the red poses in Figure 2b).

Next, we inpaint the scene from all chosen camera poses following Section 3.1. Similar to Fridman *et al.* [18], we observe it is important to clean the inpainting masks, because our text-to-image generator can generate better results for large connected regions. Thus, we first inpaint small holes with a classical inpainting algorithm [83] and dilate the remaining holes. We additionally remove all faces that fall into the dilated region and are close to the rendered depth. Please see the supplemental material for more details.

Finally, we run Poisson surface reconstruction [33] on the scene mesh. This closes any remaining holes after completion and smoothens out discontinuities. The result is a watertight mesh of the generated scene, that can be rendered with classical rasterization.

4. Results

Implementation Details. We implement mesh rasterization and fusion with Pytorch3D [59]. As our text-to-image model $\mathcal{F}_{t2i}$, we utilize a Stable Diffusion [65] model, that is finetuned on the image inpainting task, using additional mask input. We generate a single inpainting proposal and employ a state-of-the-art guided diffusion sampler [43]. As our monocular depth estimator $\mathcal{F}_d$, we employ an IronDepth [4] model, that is trained on indoor scenes from the ScanNet dataset [13] and augment it for depth inpainting according to Bae *et al*. [4]. We set δ_{edge}=0.1 and δ_{sn}=0.1 in all our experiments. During generation, we use 20 different trajectories with 10 frames each sampled between the respective start and end poses. We construct prompts using the guidelines suggested by Pierre [55]. Creating one scene takes approximately 50 minutes on one RTX 3090 GPU.

Baselines. To the best of our knowledge, there are no direct baselines that generate textured 3D room geometry from text. We compare against four related methods (please see the supplemental material for more details about baselines).

- *PureClipNeRF* [38]: We compare against text-to-3D methods for generating objects [56, 41, 29, 38, 88] and choose Lee *et al*. [38] as open-source representative.
- *Outpainting* [58, 53]: We combine outpainting from a Stable Diffusion [65] model with depth estimation and triangulation to create a mesh from an enlarged viewpoint.
- *Text2Light* [11]: We generate RGB panoramas from text using Chen *et al*. [11]. Estimating 3D mesh structure from a panorama is difficult. Related approaches estimate room layout [93], perform view synthesis [36, 26, 21, 27] or predict 360° depth [2, 31]. We perform depth prediction and subsequently apply our mesh fusion step.
- *Blockade* [37]: We apply *Blockade* [37], which uses a text-to-image diffusion model to produce more expressive RGB panoramas. We then extract the mesh similarly.

Evaluation Metrics. The generated 3D geometry is evaluated both quantitatively and qualitatively. We calculate CLIP Score (CS) [57] and Inception Score (IS) [68] on RGB renderings of the respective scenes. Additionally, we conduct a user study and ask n=61 users to score Perceptual Quality (*PQ*) and 3D Structure Completeness (*3DS*) of the whole scene on a scale of $1-5$.

Method	2D Metrics		User Study	
	CS ↑	IS ↑	PQ ↑	3DS ↑
PureClipNeRF [38]	24.06	1.26	2.34	2.38
Outpainting [58, 53]	23.10	1.60	2.90	2.58
Text2Light [11]+Ours	25.99	2.21	2.82	2.97
Blockade [37]+Ours	26.29	2.13	3.35	3.36
Ours w/o alignment	26.73	1.78	3.12	2.96
Ours w/o stretch removal	27.72	1.86	3.28	3.75
Ours w/o completion	27.97	2.18	3.72	3.87
Ours	**28.02**	**2.31**	**4.01**	**4.19**

Table 1. **Quantitative comparison.** We report 2D metrics and user study results, including: Clip Score (*CS*), Inception Score (*IS*), Perceptual Quality (*PQ*), and 3D Structure Completeness (*3DS*). Our method creates scenes with the highest quality.

4.1. Qualitative Results

We show top-down views into the scene and RGB renderings from within for our method and baselines in Figure 6. We show additional results of our method in Figure 5. *PureClipNeRF* [38] creates the key objects of the given text prompt, but does not create a complete 3D structure with floor, walls and ceilings. *Outpainting* [58, 53] creates high-detail textures, but projection from a single viewpoint creates holes due to occlusion and hinders the creation of complete 3D geometry. *Text2Light* [11] and *Blockade* [37] both create a high-detail 360° view of a complete scene, but occlusions that cannot be resolved from a single panoramic viewpoint lead to holes in the extracted 3D geometry.

In contrast, our approach creates high-detail textures and geometry, that are fused into a complete 3D scene mesh without holes. The resulting scenes contain flat floors, walls and ceilings, as well as 3D object geometry distributed throughout the scene. When specifying text prompts with a huge variety, the resulting scene contains a diverse set of objects. Please see the supplemental material for more scenes, animated results, intermediate outputs of our baselines (such as the panoramic images) as well as top-down views of meshes, that contain the reconstructed ceilings.

4.2. Quantitative Results

We show quantitative results averaged over multiple scenes in Table 1. We render 60 images from novel viewpoints for each scene to calculate the 2D metrics. We present users with multiple top-down views and renderings for each scene and let them rate each method individually (no side-by-side comparison). Stretched-out geometry and holes in the 3D geometry lead to lower scores for the baselines in all image-based metrics. Our approach achieves the highest scores, because the renderings are complete from arbitrary novel poses, satisfy the given text-prompt and

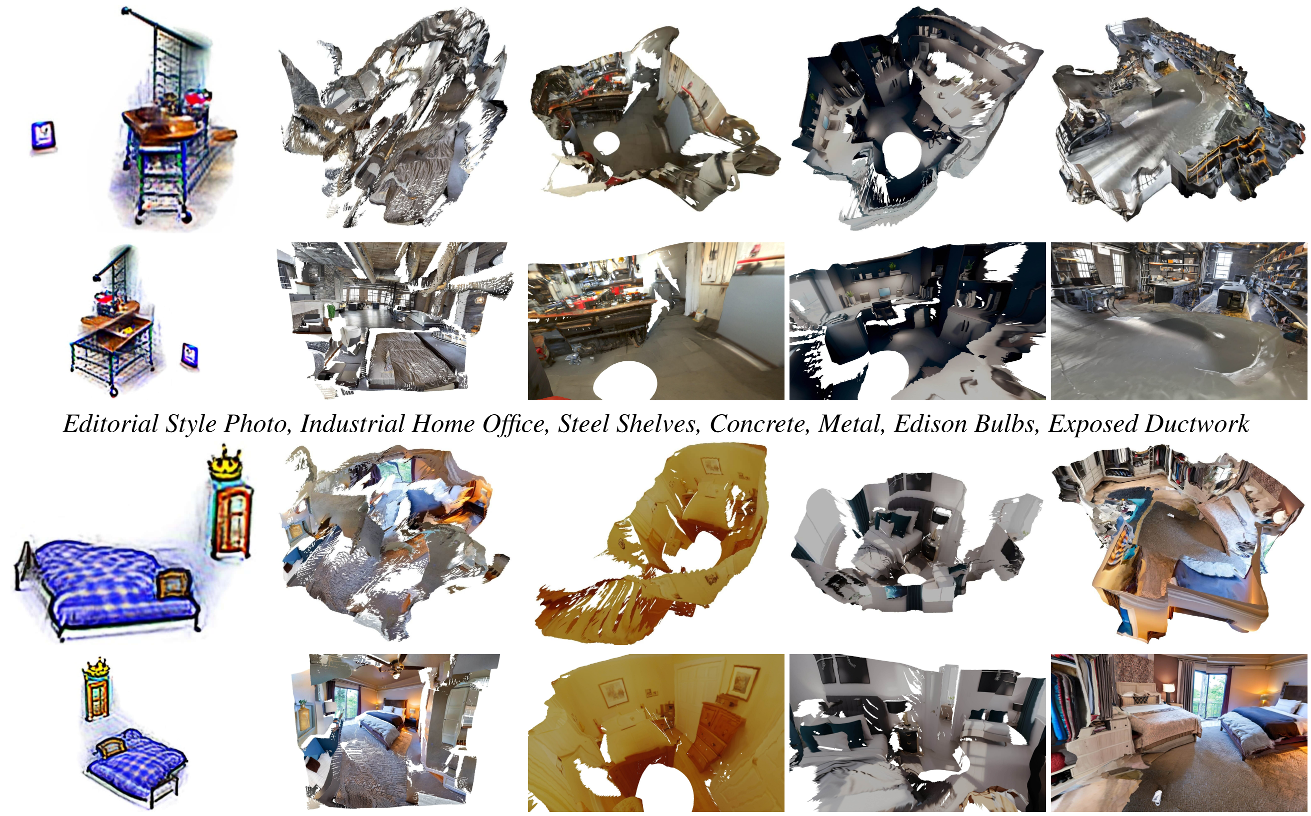
Editorial Style Photo, Coastal Bathroom, Clawfoot Tub, Seashell, Wicker, Mosaic Tile, Blue and White

A living room with a lit furnace, couch, and cozy curtains, bright lamps that make the room look well-lit

Editorial Style Photo, Modern Living Room, Large Window, Leather, Glass, Metal, Wood Paneling, Apartment

Editorial Style Photo, Modern Nursery, Table Lamp, Rocking Chair, Tree Wall Decal, Wood, Cotton, Faux Fur

Figure 5. **3D scene generation results of our method.** We show color and shaded geometry renderings from generated scenes with corresponding text prompts. Our method synthesizes realistic meshes satisfying text descriptions. We remove the ceiling in the top-down view for better visualization of the scene layout.



Editorial Style Photo, Industrial Home Office, Steel Shelves, Concrete, Metal, Edison Bulbs, Exposed Ductwork

a bedroom with a king-size bed and a large wardrobe

PureClipNeRF [38] Outpainting [58, 53] Text2Light [11]+Ours Blockade [37]+Ours Ours

Figure 6. **Qualitative comparison of our method and baselines.** *PureClipNeRF* [38] cannot produce immersive scenes with floors and walls. *Outpainting* [58, 53] does not produce 3D consistent scenes. *Text2Light* [11] and *Blockade* [37] both have holes due to occlusions. In contrast, our method creates complete meshes without holes and high details. We remove the ceiling in the top-down view for better visualization of the scene layout.

contain high-resolution image features. Users prefer our method, which highlights the quality of our accurate and complete geometry, as well as the RGB texture.

4.3. Ablations

The key ingredients of our method are depth alignment (Section 3.2), mesh fusion (Section 3.3) and the two-stage viewpoint selection (Section 3.4). We demonstrate the importance of each component in Figure 7 and Table 1.

Depth alignment creates seamless scenes. Monocular depth predictions from subsequent frames can be inconsistent in scale. This leads to disconnected components in the mesh that are backprojected from multiple viewpoints (see Figure 7a). Our depth alignment strategy allows fusing multiple frames into a seamless mesh, eventually creating a complete scene with flat floors, walls, ceilings and no holes.

Stretch removal creates undistorted scene geometry. During mesh fusion, we update the scene geometry with the contents of the next frame. Due to noisy depth prediction, the objects become stretched out, if they are observed from small grazing angles. Thus, we propose two filters (edge length and surface normal thresholds) that alleviate this issue. Instead of baking in stretched-out geometry (see Figure 7b), we disregard the corresponding faces and let the object be completed from a more suitable, later viewpoint.

Two-stage generation creates complete scenes. Our approach chooses camera poses in two stages to create a complete scene without holes. After generating the scene from predefined trajectories, the scene still contains some holes (see Figure 7c). Because the scene is built-up over time, it is impossible to choose camera poses *a-priori*, that view all unobserved regions. To this end, our completion stage samples poses *a-posteriori* to refine those regions. The resulting mesh is watertight and contains no holes (see Figure 7d).

4.4. Spatially Varying Scene Generation

Our method can be applied to generate a scene as the combination of multiple text prompts. Specifically, we use separate text prompts for different poses, crafting a set of trajectories that spatially combines scene descriptions. This

living room, couches, curtains, lit furnace, lamps

(a) Ours w/o alignment (b) Ours w/o stretch removal (c) Ours w/o completion (d) Ours (full)

Figure 7. **Ablation study on the key components of our method.** Without depth alignment (see Section 3.2), different parts of the scene are disconnected and do not fuse into a seamless mesh. Without edge and surface normal thresholds (see Section 3.3), many faces are stretched out unnaturally. Without completion (see Section 3.4), the mesh has holes in remaining unobserved regions. Our full pipeline creates complete, high-resolution scenes. We remove the ceiling in the top-down view for better visualization of the scene layout.

kitchen, dinner table, dishwashers, ovens, countertops
living room, lit furnace, couch, curtains

bathroom, shower, bathtub
bedroom, king-size bed, wardrobes

Figure 8. **Spatially varying scene generation.** Our method can create rooms with multiple parts by prompt mixing. We use separate prompts for cameras viewing different parts of the scene. This is a controllable way to create rooms from multiple descriptions.

can be desired to avoid repeating elements in a complete scene (e.g., multiple couches could be spread out over the whole room when using the same prompt for every camera). Instead, users can specify different object positions through different camera poses and text prompts. It can also be used to design a house comprised of multiple rooms, each with a different type (e.g., a living room that leads to a kitchen).

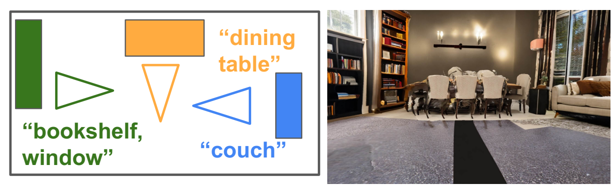


Figure 9. **Scene generation with layout guidance.** Our method can generate scenes from layout guidance. Left: we describe objects with different prompts for cameras facing at different directions. Right: the generated part of the room.

We show results that combine multiple text prompts in Figure 8 and Figure 9.

We note that the layout can only be partially controlled by the camera poses, since scene generation can create chunks with larger or smaller extent. We believe this demonstrates an exciting application of our method, that can be further explored in future work.

4.5. Limitations

Our approach allows to generate 3D room geometry from arbitrary text prompts that are highly detailed and contain consistent geometry. Nevertheless, our method can still fail under certain conditions (see supplemental material). First, our thresholding scheme (see Section 3.3) may not detect all stretched-out regions, which may lead to remaining distortions. Additionally, some holes may still not be completed fully after the second stage (see Section 3.4), which results in over-smoothed regions after applying poisson reconstruction. Our scene representation does not decompose material from lighting, which bakes in shadows or bright lamps, that are generated from the diffusion model.

5. Conclusion

We have shown a method to generate textured 3D meshes from only text input. We use text-to-image 2D generators to create a sequence of images. The core insight of our method is a tailored viewpoint selection, that allows to create a 3D mesh with seamless geometry and compelling textures. Specifically, we lift the images into a 3D scene, by employing our alignment strategy that iteratively fuses all images into the mesh. Our output meshes represent arbitrary indoor scenes that can be rendered with classical rasterization pipelines. We believe our approach demonstrates an exciting application of large-scale 3D asset creation, that only requires text as input.

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