

Robust 3D Shape Reconstruction in Zero-Shot from a Single Image in the Wild

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<https://ZeroShape-W.github.io>

Abstract

Recent monocular 3D shape reconstruction methods have shown promising zero-shot results on object-segmented images without any occlusions. However, their effectiveness is significantly compromised in real-world conditions, due to imperfect object segmentation by off-the-shelf models and the prevalence of occlusions. To effectively address these issues, we propose **a unified regression model** that integrates segmentation and reconstruction, specifically designed for occlusion-aware 3D shape reconstruction. To facilitate its reconstruction in the wild, we also introduce **a scalable data synthesis pipeline** that simulates a wide range of variations in objects, occluders, and backgrounds. Training on our synthetic data enables the proposed model to achieve state-of-the-art zero-shot results on real-world images, using significantly fewer parameters than competing approaches.

1. Introduction

The abundance of large-scale 3D shapes [4, 7, 9, 10, 16, 33] has enabled the development of reconstruction models with strong generalization capabilities, even allowing for zero-shot monocular 3D shape reconstruction [25, 29, 41, 66, 68, 74]. However, these models are not deployable in real-world settings, as they assume object images that have no backgrounds and occlusions. Thus, they utilize *off-the-shelf* segmentation models [32, 60] to handle in-the-wild images. This dependency introduces two main challenges: (i) error accumulation by off-the-shelf models, and (ii) removal of occluded object parts by segmentation. Both issues hinder precise shape reconstruction, as shown in Figure 1.

To tackle the challenges, we propose **ZeroShape-W**, an occlusion-aware 3D shape reconstruction model (Fig. 2a). Our model jointly regresses the silhouettes of a salient object and its occluders, along with a depth map and camera intrinsics to estimate the object’s visible 3D shape. Then, its full 3D shape is reconstructed by using the visible 3D shape and the silhouette of occluders. This approach enables the reconstruction of occluded object parts, making it effective

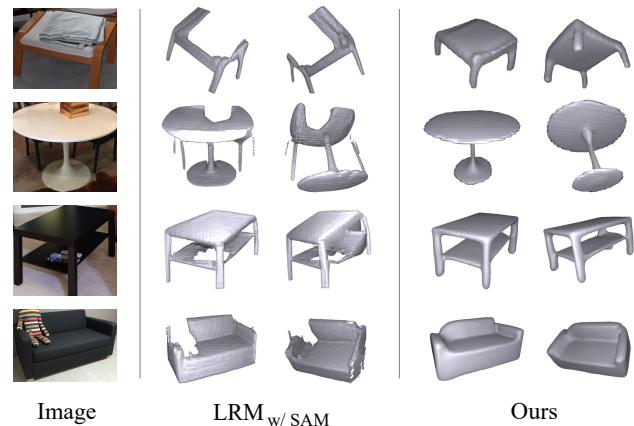


Figure 1. Single-view 3D shape reconstruction on real-world images [65]. Compared with LRM [25] that requires an off-the-shelf segmentation model (e.g., SAM [32]), our approach not only eliminates the need for such an additional model but also achieves greater robustness to occlusions.

in real-world conditions. However, a significant challenge remains: *how can we train our model for robust zero-shot reconstruction in the wild?* To achieve this goal, we need large-scale diverse data that can cover various real environments. Unfortunately, the availability of real-world images annotated with precise 3D shapes is limited. An alternative approach is to generate realistic renderings from 3D object collections [4, 7, 9, 10, 16], but this is also limited by the availability of high-quality synthetic assets.

In this paper, we introduce a scalable data synthesis pipeline (Fig. 2b) that simulates a wide range of variations using generative models, thereby removing the reliance on limited real-world data or high-quality synthetic assets. Our pipeline first synthesizes foreground object images using a conditional generative model [86], with spatial conditions obtained by rendering 3D shapes available from extensive object collections [4, 9, 10]. Then, their backgrounds are generated by an object-aware background outpainting model [13]. For these synthesized images, we apply Copy-Paste augmentation [19] to simulate occluders on-the-fly during model training.

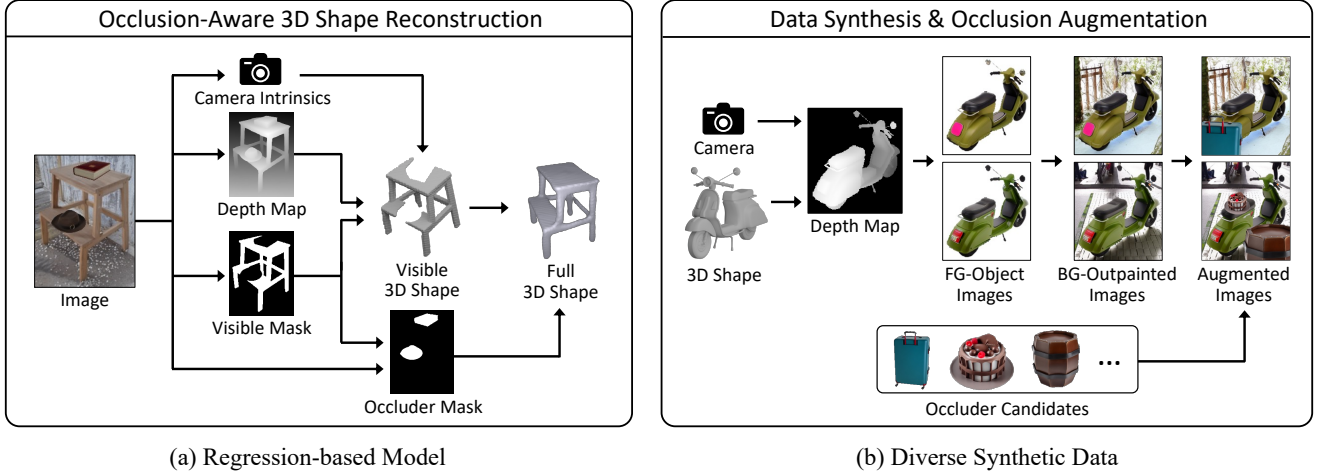


Figure 2. Proposed approach for zero-shot monocular 3D shape reconstruction in the wild. (a) Our model reconstructs the full 3D shape of a salient object using its visible 3D shape and the silhouette of its occluders. The visible 3D shape is estimated from camera intrinsics, depth map, and visible region of the object. (b) We create our training dataset by synthesizing diverse data. We render 3D shapes and then simulate their appearances and backgrounds using generative models. Occluders are inserted on-the-fly during model training.

By training the proposed model on our diverse synthetic data, we expose it to a wide variety of foreground objects, their occluders, and backgrounds. This process enables our model to focus on learning to capture domain-invariant and object-centric geometric priors. In this way, we improve its generalization across various environments.

To validate the effectiveness of our approach, we first create our training dataset by synthesizing diverse images using 3D shapes from Objaverse [10] and ShapeNet [4]. Then, we train our model on the data augmented with occlusions. We evaluate the model on the real-world benchmark, Pix3D [65], where it outperforms state-of-the-art models while using significantly fewer model parameters. In addition to the benchmark, we also qualitatively evaluate the proposed model on in-the-wild images from ObjectNet [2], OfficeHome [72], and PACS [35].

2. Related Work

Single-view 3D shape reconstruction in the wild. This task aims to estimate the 3D shape of an object from a single image captured in a real-world environment. It is challenging because objects exhibit a variety of 3D shapes while their appearances are greatly altered by environmental factors. To handle such variations, 3D shape reconstruction models [1, 6, 18, 20–23, 25, 28–30, 38, 41, 48, 50, 53, 66, 68, 70, 73, 74, 76–78, 80, 81, 83, 85, 88] should generalize well across various environments. However, the scarcity of real-world 3D data poses a significant obstacle in pursuing this goal. In this paper, we address this issue by synthesizing large-scale data using generative models.

Single-view reconstruction methods fall into two categories: generative model-based approaches [41, 66, 74, 81] and regression-based approaches [25, 29, 68]. The genera-

tive model-based approaches synthesize multi-view images using diffusion models such as Zero-1-to-3 [39], which are effective to estimate 3D shapes with textures but incur significant computational costs. In contrast, regression-based approaches such as ZeroShape [29] estimate 3D shapes in a single forward pass, offering much greater efficiency.

Recent state-of-the-art methods in both approaches assume clean object-segmented images without occlusions, making them difficult to operate in real-world settings. In this work, we tackle this issue by introducing a unified regression model that both segments and reconstructs while accounting for occlusions. To the best of our knowledge, our work is the first regression-based approach for zero-shot single-view 3D shape reconstruction in the wild.

Improving model robustness to distribution shifts. It is common to exploit multiple domains for learning domain-invariant features [3, 12, 31, 34, 36, 44, 45, 63, 90, 91] to enhance the model robustness. However, multiple domains from real-world environments might not be accessible. To effectively tackle this issue, domain randomization methods [8, 14, 26, 46, 56, 61, 67, 69, 84] synthesize multiple domains via a random simulation of diverse scenarios. By exposing a model to randomized variations, it learns to capture generalizable representations capable of handling a wide range of variations encountered in real-world settings.

Following the paradigm of domain randomization, we simulate diverse variations in foreground objects, occluders, and backgrounds. However, this is not done completely randomly, as the background outpainting model [13] generates backgrounds while considering the foreground objects. By training the proposed model on our data, it could learn to capture domain-invariant and object-centric geometric priors, which are useful for handling diverse objects.

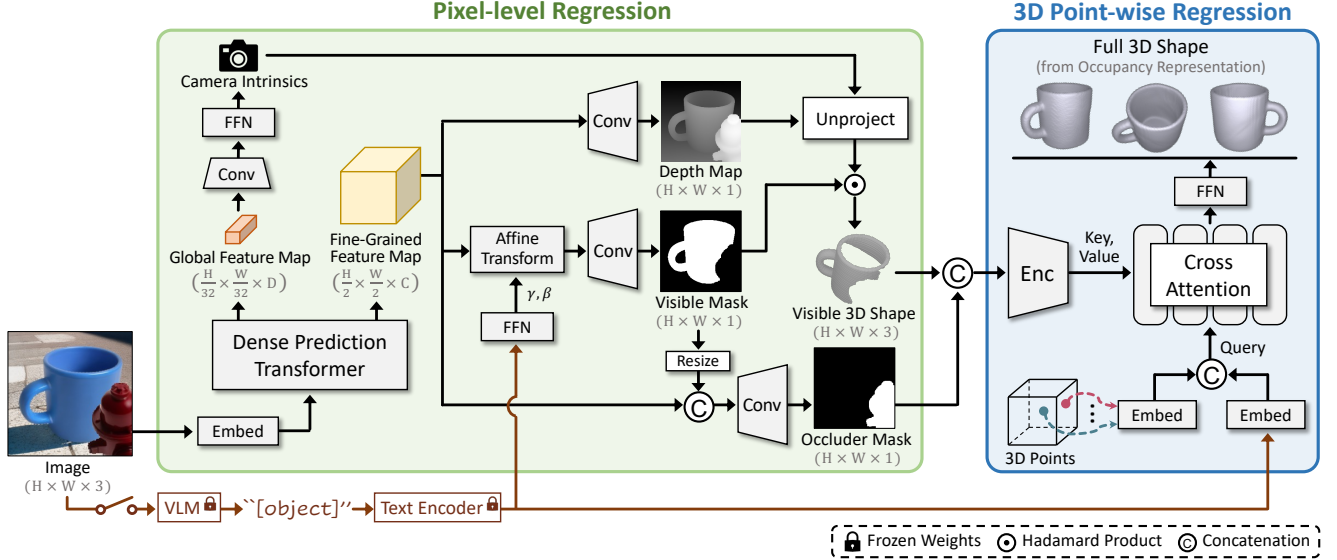


Figure 3. Overall architecture of ZeroShape-W. Given an object-centric RGB image, our model leverages the backbone of Dense Prediction Transformer (DPT) [59] to regress camera intrinsics, a depth map, a visible mask of a salient object, and an occluder mask that represents the object’s occluders. These components are used to derive the object’s visible 3D shape, which is then combined with the occluder mask to regress occupancy values of 3D point queries through cross-attention layers [71]. This process recovers the object’s full 3D shape, including occluded object parts. To alleviate difficulties of in-the-wild reconstruction, we optionally incorporate open-set category priors by estimating the object’s category, “[object]” (e.g., “cup”), using an additional vision-language model (VLM) [37].

Synthetic data generation. To train 3D shape reconstruction models, we can synthesize data by rendering 3D objects from extensive object collections [4, 7, 9, 10, 16, 33] via computer graphics tools. As long as sufficient 3D shape and texture assets are available for objects and environments, this approach could also facilitate 3D shape reconstruction in the wild. However, it is expensive to collect a great variety of high-quality assets (e.g., 4K-resolution texture maps, HDR environment maps) needed to bridge the gap between synthetic and real environments. Moreover, the diversity of object appearances and backgrounds depicted by rendered images is determined by the combination of available assets. Compared with these computer graphics tools, our data synthesis pipeline could simulate more diverse object appearances and backgrounds without relying on such additional high-quality assets, by leveraging generative models pre-trained on large-scale datasets.

Generative models with 3D assets. Recent works [17, 43, 87] use conditional generative models [49, 57, 86] to synthesize images with 3D assets for various tasks, e.g., object pose estimation. Compared with them, accurate preservation of silhouettes within spatial conditions is more crucial for 3D shape reconstruction. To better preserve silhouettes, our data synthesis pipeline employs a two-step generation process. We utilize an initial guidance for foreground object synthesis and exploit a background outpainting model [13] specifically designed for preserving silhouettes. In this way, each synthesized image is paired with its precise 3D shape.



Figure 4. Effect of using an occluder mask. It enables full 3D shape reconstruction, even for occluded object parts. Note that existing state-of-the-art methods [25, 29, 41, 66, 68, 74] struggle with occlusions, as they assume the salient visible object in the current view is unobstructed.

3. Method

The proposed ZeroShape-W (Fig. 3) aims to regress the full 3D shape of a salient object from a single image, including its visible and occluded parts (Fig. 4). Inspired by [29, 75], our model first regresses pixel-level information, which is used as condition to regress occupancy values of 3D point queries. These occupancy values represent the visible and hidden geometry of the salient object, while also accounting for occluded regions that were not addressed in [29, 75].

During pixel-level regression, our model regresses a depth map, a visible mask of the object, and an occluder mask that depicts the object’s occluders. It also estimates camera intrinsics to convert depth values into the object’s visible 3D shape in a viewer-centric coordinate system.

During 3D point-wise regression, our model regresses occupancy values of 3D point queries through cross-attention layers [71], utilizing features from the visible 3D shape and occluder mask as keys and values. This approach

can effectively reconstruct the object’s hidden geometry, with the help of learned 3D shape priors.

For in-the-wild images, identifying arbitrary salient objects is often challenging due to complex backgrounds or occlusions, which can result in noisy mask estimations. In such cases, visible 3D shapes may mistakenly include background geometries. To address these issues, we optionally incorporate category-specific priors by leveraging a vision-language model [37] and CLIP text encoder [58]. Specifically, the vision-language model generates a **category-specific prompt** “[object]” (e.g., “cup” in Fig. 3) that describes the salient object in the input image. For stable inference with unseen object categories, we use an averaged CLIP text embedding obtained from the category-specific prompt and a **category-agnostic prompt** “object”. In cases where the category-specific priors are not used, our model relies solely on the category-agnostic prompt without estimating the object’s category.

3.1. Pixel-level Regression

For an object-centric RGB image $I \in \mathbb{R}^{H \times W \times 3}$, we first obtain image embeddings $\mathbf{E}_I \in \mathbb{R}^{(H/16) \times (W/16) \times D}$ using ResNet50 [24], as done in ViT-Hybrid [11]. Then, we feed the embeddings $\mathbf{E}_I$ into the backbone of Dense Prediction Transformer (DPT) [59]. From the backbone, we extract a global feature map $\mathbf{X}_G \in \mathbb{R}^{(H/32) \times (W/32) \times D}$ and a fine-grained feature map $\mathbf{X}_F \in \mathbb{R}^{(H/2) \times (W/2) \times C}$. The global feature map $\mathbf{X}_G$ is the reassembled output from the last transformer layer in DPT, while the fine-grained feature map $\mathbf{X}_F$ is the output from the last fusion layer in DPT.

Camera intrinsics. To regress the visible 3D shape of the salient object, we estimate camera intrinsics $K \in \mathbb{R}^{3 \times 3}$ from the global feature map $\mathbf{X}_G$. Specifically, we obtain the camera intrinsics K by predicting a focal length scaling factor and principal point shifts, as done in [29]. The scaling factor adjusts a base focal length according to the image resolution $H \times W$, and the principal point shifts are also specified relative to the image resolution. These parameters are estimated from the global feature map $\mathbf{X}_G$ using shallow convolutional layers, a pooling layer, and a feed forward network (FFN).

Depth map. To derive the visible 3D shape by unprojecting depth values using the estimated camera intrinsics K , we regress a depth map $\mathbf{M}_D \in \mathbb{R}^{H \times W \times 1}$ from the fine-grained feature map $\mathbf{X}_F$. For this regression, we use shallow convolutional layers with interpolation.

Visible mask. To identify the visible region of the salient object, we regress a visible mask $\mathbf{M}_V \in \mathbb{R}^{H \times W \times 1}$ from the fine-grained feature map $\mathbf{X}_F$. For precise regression, we adaptively adjust the fine-grained feature map $\mathbf{X}_F$ based on the object’s category. Inspired by [25, 54, 55], we modulate the feature map using an affine transformation with a scaling factor $\gamma \in \mathbb{R}^C$ and a shift factor $\beta \in \mathbb{R}^C$, estimated

by an FFN with CLIP text encoder [58]. We modulate the feature map $\mathbf{X}_F$ at each spatial location (i, j) as follows:

$$\bar{\mathbf{X}}_{F_{ij}} = (1 + \gamma)\mathbf{X}_{F_{ij}} + \beta, \quad (1)$$

where $\bar{\mathbf{X}}_F \in \mathbb{R}^{(H/2) \times (W/2) \times C}$. From this modulated feature map, we regress the visible mask $\mathbf{M}_V$ using shallow convolutional layers with interpolation.

Visible 3D shape. Using the estimated camera intrinsics K , depth map $\mathbf{M}_D$, and visible mask $\mathbf{M}_V$, we derive the visible 3D shape $\mathbf{S}_V \in \mathbb{R}^{H \times W \times 3}$ that contains (x, y, z) -coordinates of each pixel location (i, j) as follows:

$$\mathbf{S}_{V_{ij}} = \mathbb{1}_{\{\mathbf{M}_{V_{ij}} \geq \eta\}} \cdot (\mathbf{M}_{D_{ij}} K^{-1} [i, j, 1]^\top), \quad (2)$$

where $\mathbb{1}_{\{\cdot\}}$ is an indicator function, and η denotes a threshold. We normalize $\mathbf{S}_V$ to have a zero mean and a unit scale.

Occluder mask. To determine the object’s occluded region, we regress an occluder mask $\mathbf{M}_O \in \mathbb{R}^{H \times W \times 1}$ using the fine-grained feature map $\mathbf{X}_F$ and visible mask $\mathbf{M}_V$. Specifically, we resize the visible mask to the resolution of $H/2 \times W/2$, and concatenate it with the feature map along the channel dimension. Then, we regress the occluder mask $\mathbf{M}_O$ using shallow convolutional layers with interpolation.

3.2. 3D Point-wise Regression

We regress occupancy values of 3D point queries using cross-attention layers to effectively consider local features from pixel-level estimations.¹ We begin by concatenating the visible 3D shape $\mathbf{S}_V$ and the occluder mask $\mathbf{M}_O$ along the channel dimension, which is then fed into an encoder. It produces Z -dimensional vectors that serve as keys and values in cross-attention layers.

For each 3D point query, we construct a Z -dimensional query vector by concatenating two $Z/2$ -dimensional embeddings: one from the point’s (x, y, z) -coordinates and the other from CLIP text encoder [58]. The query vectors are processed through L cross-attention layers, where each query independently attends to its relevant spatial features. Then, to reconstruct the object’s full 3D shape, we estimate the occupancy value of each query using an FFN.

3.3. Loss

We train our model using binary cross-entropy losses with the estimated visible mask $\mathbf{M}_V$, occluder mask $\mathbf{M}_O$, and occupancy values. For the estimated depth map $\mathbf{M}_D$, we apply a scale- and shift-invariant MAE loss [15] over two regions: (i) the visible mask region with ground-truth depth and (ii) the entire region with pseudo depth estimated from a pre-trained model, referred to as the auxiliary depth loss. This auxiliary loss addresses the limitation of our data synthesis pipeline, which only provides depth for object areas. For the estimated camera intrinsics K , we use an MSE loss by comparing the visible 3D shape $\mathbf{S}_V$ to the ground truth.

¹We extend prior works [29, 75] to reconstruct occluded object parts.

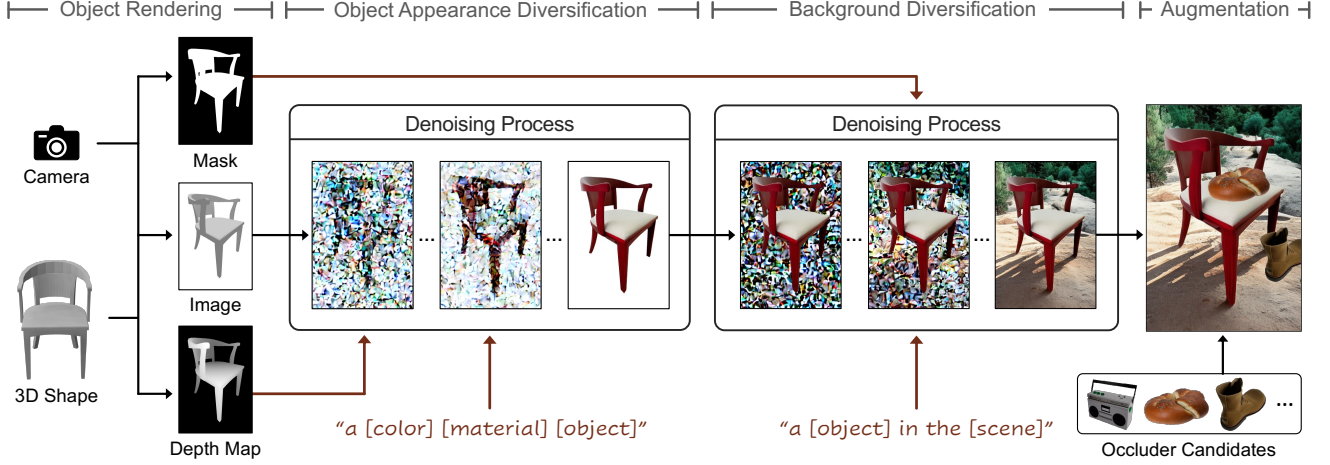


Figure 5. Overview of our data synthesis. Given a camera and 3D object, we render it to obtain an object mask, image, and depth map. We simulate object appearances via a conditional diffusion model [86] using the depth as its spatial condition and “a [color] [material] [object]” (e.g., “a red wood chair”) as its textual condition. To alleviate shape distortion by the generative model, we use the rendered image as initial guidance. We simulate its background via an object-aware background outpainting model [13] using the mask and “a [object] in the [scene]” (e.g., “a chair in the canyon”) as its textual condition. Then, we put occluders during data augmentation.

3.4. Implementation Details

We input an image of resolution $H \times W$, where $H = W = 224$. Using DPT-Hybrid [59], we extract the D -dimensional feature $\mathbf{X}_G$ and C -dimensional feature $\mathbf{X}_F$, where $D = 768$ and $C = 256$. In eq. (2), we set $\eta = 0.5$. In L cross-attention layers, we employ Z -dimensional vectors, where $L = 2$ and $Z = 256$. During training, we use Depth Anything V2 [82] for the auxiliary depth loss. At inference time, we optionally use LLaMA-VID [37] to identify the object’s category. Further details can be found in the supplementary material.

4. Data Synthesis

Our scalable data synthesis pipeline (Fig. 5) produces diverse images, along with their corresponding 3D shapes, camera parameters, depth maps, and masks. We use Copy-Paste [19] augmentation to insert occluders at each training iteration. Please see the supplementary material for details.

4.1. Object Rendering

A great variety of 3D shapes can be readily obtained from 3D object collections [4, 7, 9, 10, 16, 33] or generative models [5, 40, 64, 77]. In line with ZeroShape [29], we utilize the same set of 3D objects spanning over 1,000 categories, including 52K objects from ShapeNetCore.v2 [4] and 42K objects from Objaverse-LVIS [10].

Each 3D object is rendered by multiple cameras constructed with varying camera distances, elevation angles, focal lengths, and LookAt points. This rendering process produces over 1 million object images, and each output is paired with precise 3D shapes, camera parameters, depth maps, and masks.

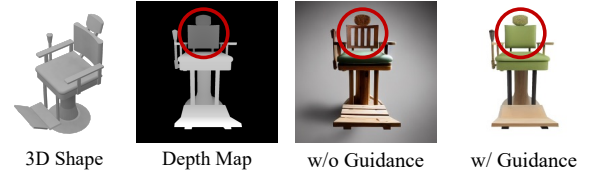


Figure 6. Effect of using an initial guidance. The guidance assists in preserving the object silhouette depicted in the spatial condition.

4.2. Object Appearance Diversification

To simulate diverse visual variations in object appearances, we employ ControlNet [86] which is a conditional diffusion model capable of realistically synthesizing diverse images. In our data synthesis, the generative model simulates a wide range of variations by using a depth map as its spatial condition and “a [color] [material] [object]” as its textual condition. Here, the placeholders [color] and [material] are replaced by words selected from pre-defined color and material lists, while [object] denotes the category of the used 3D object.

Initial guidance. The diffusion model [86] occasionally distorts the object silhouette depicted in the spatial condition. To alleviate this distortion, we utilize the rendered image as initial guidance. Motivated by SDEdit [47], we perturb the guidance with Gaussian noise and feed it to the model. Since the noisy guidance retains the original spatial structure, it effectively reduces silhouette distortion (Fig. 6).

4.3. Background Diversification

To simulate diverse backgrounds, we use an object-aware background outpainting model [13]. It adapts Stable Diffusion Inpainting 2.0 [62] by using modified ControlNet [86], allowing for background generation without extending the

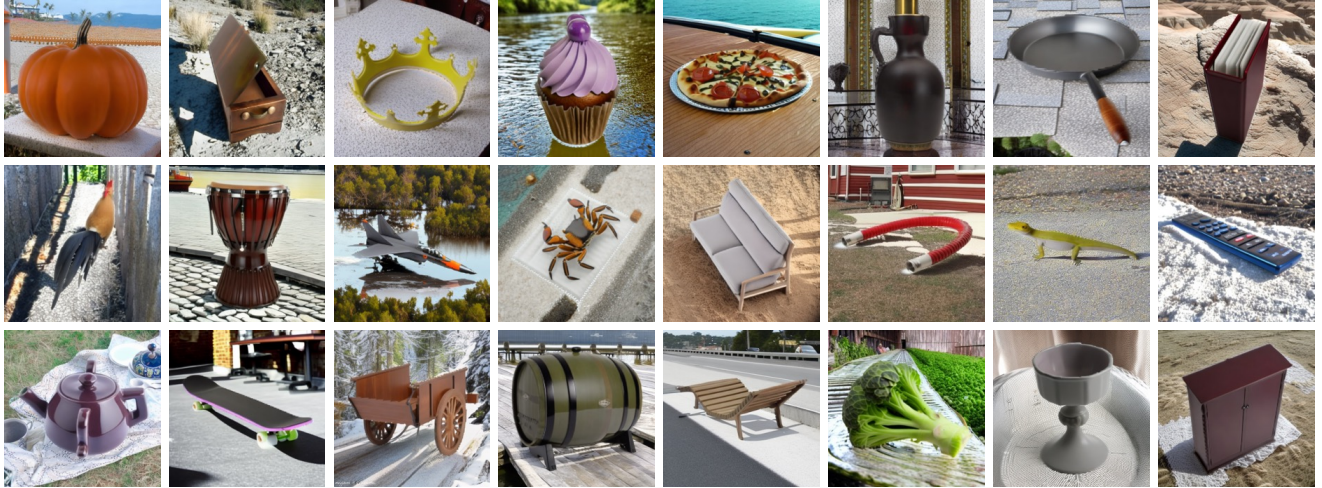


Figure 7. Diverse synthetic data produced by our scalable data synthesis pipeline. Based on 3D shape renderings from ShapeNetCore.v2 [4] and Objaverse-LVIS [10], we synthesize diverse images using ControlNet [86] and object-aware background outpainting model [13].

object’s silhouette. We generate various backgrounds using the object image, its mask, and the prompt “a [object] in the [scene]”, where [scene] is selected from scene categories [79, 89]. Ideally, it synthesizes backgrounds that appear to be captured by cameras with focal lengths similar to those used for the object’s rendering.

4.4. Augmentation

For images generated by our data synthesis (Fig. 7), we simulate occluders on-the-fly during model training via Copy-Paste augmentation [19] using our synthesized foreground objects. To enable stable estimation of camera intrinsics, we put objects rendered by similar focal lengths.

5. Experiments

5.1. Evaluation Settings

Protocol. To convert implicit 3D shape representation into explicit 3D meshes, we extract the isosurface from the implicit representation via the Marching Cubes [42] algorithm. Following [23, 50, 85], we align predicted and ground-truth meshes using the Iterative Closest Point algorithm. Then, we uniformly sample 10K points from each mesh.

Metrics. Using 10K sampled points, we compute Chamfer Distance (CD) and F-Score (FS) for quantitative evaluation, as in [27–29]. Specifically, $FS@τ$ denotes the harmonic mean of $precision@τ$ and $recall@τ$, which represents the concordance between predicted and ground-truth points within a distance threshold $τ$.

Datasets. We evaluate our model on real-world object images from Pix3D [65], ObjectNet [2], OfficeHome [72], and PACS [35]. As Pix3D is the widely recognized benchmark for 3D shape reconstruction in the wild, we use it for comparison with other state-of-the-art models [25, 29].

5.2. Experimental Results

Quantitative comparison. Currently, there is no zero-shot monocular 3D shape reconstruction model capable of directly processing in-the-wild images. Therefore, we compare our model with state-of-the-art reconstruction models, LRM [25]² and ZeroShape [29], which operate on object-segmented images without occlusions. For comprehensive comparisons with these baselines, we equip them with the off-the-shelf modal segmentation model, SAM [32], and amodal completion model, pix2gestalt [52].

In Table 1, we evaluate the baselines and our model on the Pix3D benchmark [65]. Although the proposed model does not utilize such off-the-shelf models, it substantially outperforms them. In terms of $FS@τ$, our model outperforms the strongest baseline ZeroShape_w/SAM + pix2gestalt by a large margin of 13.7% (38.2 vs. 33.6). With regard to CD, the proposed model also surpasses the strongest baseline by a large margin of 13.4% (0.097 vs. 0.110); lower is better for CD evaluation metric.

Our model requires significantly fewer parameters than the baselines, since it performs joint regression using the shared feature map $\mathbf{X}_F$. For example, the number of parameters used by our model is less than 1/12 of the parameters used by LRM_w/SAM + pix2gestalt, as shown in Table 1.

Qualitative comparison. Figure 8 presents single-view 3D shape reconstruction results on real-world images from Pix3D [65]. When existing reconstruction models [25, 29] utilize an off-the-shelf modal segmentation model [32], they struggle to estimate the geometry for occluded object parts. To enable occlusion-aware 3D reconstruction, they should incorporate an amodal completion model [52]. However,

²In this paper, we use the publicly available OpenLRM model weights from <https://github.com/3DTopia/OpenLRM>

Model	Off-the-shelf Model		Overhead	Pix3D Evaluation				
	Modal Segmentation	Amodal Completion		FS@ τ ↑	FS@ 2τ ↑	FS@ 3τ ↑	FS@ 5τ ↑	CD↓
LRM	SAM	—	> 1100M	31.0	54.5	69.9	87.1	0.121
	SAM	pix2gestalt	> 2400M	31.1	54.9	70.6	87.7	0.119
ZeroShape	SAM	—	> 800M	32.1	56.8	72.1	88.0	0.116
	SAM	pix2gestalt	> 2100M	33.6	59.0	74.2	89.2	0.110
Ours (category-agnostic)	—	—	193.7M	38.2	65.3	79.9	92.5	0.097

Table 1. Comparison of single-view 3D shape reconstruction on Pix3D [65]. Existing state-of-the-art reconstruction models, LRM [25] and ZeroShape [29], require an off-the-shelf modal segmentation model (e.g., SAM [32]), because they assume object-segmented images without any occlusions. For occlusion-aware reconstruction, they need an additional amodal completion model (e.g., pix2gestalt [52]). In this comparison, our model is evaluated using the category-agnostic prompt “object”.

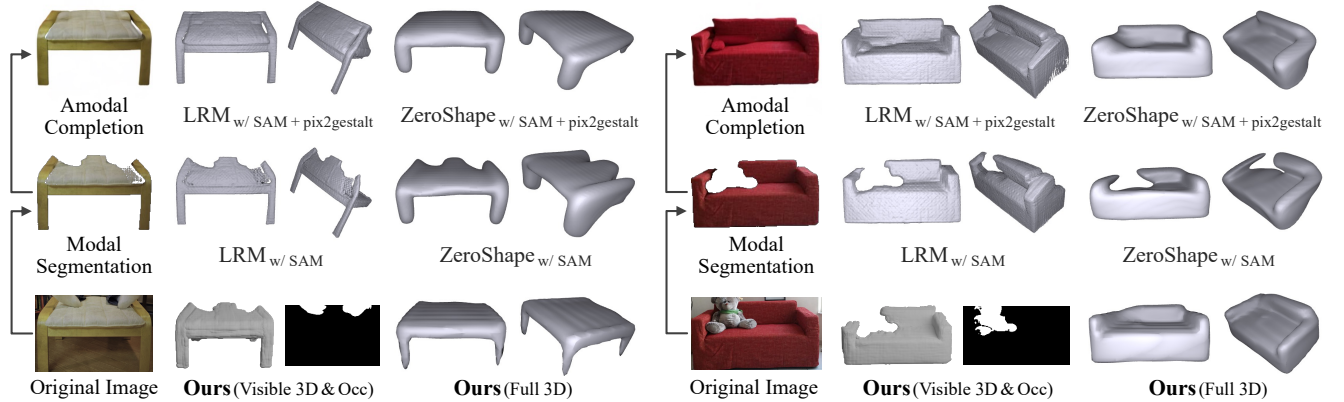


Figure 8. Comparison of single-view 3D shape reconstruction on Pix3D [65]. In this comparison, LRM [25] and ZeroShape [29] take modal segmentation results (from SAM [32]) or amodal completion results (from pix2gestalt [52]) as inputs. In contrast, our model directly takes original images as inputs, and performs occlusion-aware reconstruction by regressing visible 3D shapes and occluder silhouettes.

this approach often leads to error accumulation. Even with well-completed amodal images, shape reconstruction errors may still occur (see LRM_{w/SAM} + pix2gestalt in the left column of Figure 8). This might be due to compatibility issues with off-the-shelf models, as they were trained on different datasets. In contrast, our model achieves promising results without the need to heavily pre-process input images using the off-the-shelf models.

Evaluation on non-occluded or occluded images only. In Table 2, we compare evaluation results on non-occluded or occluded object images from the Pix3D dataset [65], which consists of 42.6% non-occluded and 57.4% occluded images. Under both scenarios, our end-to-end regression method substantially outperforms existing approaches [25, 29] that depend on an off-the-shelf model [32].

Optional category-specific priors. To evaluate the effect of incorporating such category priors, we compare results obtained using the category-agnostic prompt “object” and the category-specific prompt “[object]” (estimated by a VLM [37]). Table 3 shows that the priors improve our model’s accuracy. Please see the supplementary material for more analyses.

Model	Non-Occluded		Occluded	
	FS@ τ ↑	CD↓	FS@ τ ↑	CD↓
LRM _{w/SAM}	33.5	0.111	29.1	0.128
ZeroShape _{w/SAM}	34.6	0.106	30.2	0.123
Ours (category-agnostic)	43.6	0.082	34.2	0.107

Table 2. Quantitative evaluation exclusively on *non-occluded* or *occluded* object images from the Pix3D dataset [65].

Prompt	Pix3D Evaluation		
	FS@ τ ↑	FS@ 5τ ↑	CD↓
Category Agnostic	38.2	92.5	0.097
Category Specific (w/ VLM)	39.1	92.6	0.095

Table 3. Pix3D [65] evaluation according to category prompts. We incorporate category-specific priors by using a VLM [37].

Reconstruction of diverse objects. Figure 9 presents single-view 3D shape reconstruction results on real-world images from ObjectNet [2], OfficeHome [72], and PACS [35]. By leveraging learned priors, the proposed model can regress 3D shapes of various objects captured in real-world environments.

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