SGAM: Building a Virtual 3D World through Simultaneous Generation and Mapping

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Abstract

We present simultaneous generation and mapping (SGAM), a novel 3D scene generation algorithm. Our goal is to produce a realistic, globally consistent 3D world on a large scale. Achieving this goal is challenging and goes beyond the capacities of existing 3D generation methods, which fail to scale up to create large scenes. Video generation and view synthesis methods cannot produce a globally consistent 3D scene structure. Towards tackling the challenges, we take a hybrid approach that integrates generative sensor modeling with 3D reconstruction. Our proposed approach is an autoregressive generative framework that simultaneously generates sensor data at novel viewpoints and builds a 3D map at each timestamp. Given an arbitrary camera trajectory, our method repeatedly applies this generation-and-mapping process for thousands of steps, allowing us to create a gigantic virtual world. Our model can be trained from RGB-D sequences without having access to the complete 3D scene structure. The generated scenes are readily compatible with various interactive environments and rendering engines. Building upon the CLEVR dataset, we propose a large-scale 3D scene generation benchmark and demonstrate ours can generate consistent, realistic, and geometrically-plausible scenes that compare favorably to existing view synthesis methods.

1 Introduction

Human perception goes way beyond simple recognition and reconstruction. Our extraordinary abilities not only allow us to make sense of what we see, but also enable us to *extrapolate* and *imagine* what we do not (*e.g.*, hallucinate what the scene may possibly look like outside the image). With just a simple glance, we can effortlessly re-build a mental world, that may not be exactly like the original, but is perceived by our brain to be the same. In fact, it is such a profound ability that draws us apart from existing AI systems.

The goal of this paper is to equip computational machines with similar capabilities. We aim to develop a program that can create an arbitrarily large, realistic, and consistent *3D world* from *a single snapshot of the scene*. The task is of paramount interest to many applications in computer vision [60, 40, 74], computer graphics [65, 65], geography [5], and robotics [13, 44], since it unlocks numerous potentials. For instance, it may allow us to build an interactive virtual environment without any costly and laborious 3D modeling pipeline [12].

Indeed, there has been a consistent pursuit within the computer vision and graphics community in the past few decades [17, 16, 85, 65, 9, 68, 72], where people attempt to design algorithms and models that are capable of extrapolating and hallucinating the world from a single input image. Unfortunately, a large body of efforts have been focusing on modeling in the 2D image space [17, 16, 85, 18, 37, 9], or require external 3D assets and manually specified rules for restricted 3D generation [10]. Recently, with the advent of deep generative models [36, 76, 40, 61, 60], researchers have made great strides in unconstrained 3D syntheses. However, due to the highly complex structure of the task, these approaches mostly focus on object-centric scenarios, or generating small-scale environments.

Submitted to 36th Conference on Neural Information Processing Systems (NeurIPS 2022). Do not distribute.

Figure 1: **A large-scale virtual world created after 2000 SGAM steps**. SGAM is an auto-regressive generative framework that simultaneously generates sensor data at novel views and builds a 3D map.

With these problems in mind, we present Simultaneous Generation and Mapping (SGAM), a novel 3D scene generation algorithm. SGAM builds upon insights from state-space representation in SLAM [48, 23] as well as recent generative models [73, 18, 66]. At its core lies two key modules: (i) *a generative sensor module* that takes a scene representation and a novel query viewpoint as input and renders a photo-realistic RGB-D image of a 3D scene; and (ii) *a mapping module* that exploits the newly generated RGB-D observation at a given camera pose and updates the scene representation. Given an arbitrary camera trajectory, our method iteratively applies this procedure to construct the 3D scene. By grounding scene generation with "a map", we are able to produce realistic and spatially consistent 3D world at a significantly larger scale than any previous 3D generation effort without drifting or collapsing. Additionally, our generated scenes can be represented explicitly as textured 3D models, making them readily compatible with various interactive environments and rendering engines. We note that we are not the first to tackle the task of scene synthesis under large viewpoint differences [56, 60, 40]. Several recent efforts have demonstrated promising results in this direction, from which our method is inspired. Nonetheless, these works do not produce a consistent 3D scene representation of the infinite world and potentially suffer from mode collapse [60, 40].

We validate the efficacy of our method on two novel large-scale 3D scene datasets, Clevr-infinite and GoogleEarth. Both benchmarks produce substantially larger 3D scenes than existing datasets. This allows us to benchmark large-scale 3D scene generation. We evaluate the standard metrics for reference-based and non-reference-based perceptual image quality, such as PSNR, SSIM [75], LPIPS [82], IS [63], and FID [27]. We further benchmark the realism of the generated 3D scenes in terms of Jensen-Shannon divergence and maximum-mean discrepancy [22]. Our experimental results suggest that 1) our method could produce more realistic results than existing single-image novel view synthesis methods; 2) our approach can generate a more meaningful 3D world than the prior perpetual view generation algorithms.

2 Related Work

Image generation: How to synthesize an image realistically has been a long-standing problem in computer vision. The task dates back to 60s [32, 4] where researchers attempted to generate textures by matching statistics [42, 26]. Through parametric sampling [85] or non-parametric matching [17, 16], they were able to synthesize an infinite amount of high-fidelity texture images. Unfortunately, these approaches fall short when applied to natural images, since the images have much higher complexity. Recently, with the help of deep generative models [21, 35, 55, 28, 66], researchers have demonstrated promising results on generating photo-realistic images [30, 33, 34]. With proper design and inductive biases [73, 18, 11], they are even able to scale the output to mega-pixel level [70, 9]. In this paper, we build our generation module on top of VQ-GAN [18]. However, instead of treating scene generation as a pure 2D task as in the past, we explicitly consider the relationship between appearance and geometry — both at the input level and the output level. By encoding both information into the quantized codebook, we are able to "grow" the 3D scene from an initial seed image and generate a boundless world, which is not exactly like the original, but will be perceived by humans to be the same region.

3D Generation: 3D modeling and synthesis have been an active yet challenging research problem for decades [8, 6, 68]. Recently, with the development of image generation techniques [21, 35, 57], the field has experienced a rapid growth [78, 49, 69]. Drawing inspiration from its corresponding 2D analogue, researchers have been able to generate high quality point clouds [38, 79, 7], voxels [19, 77], meshes [24, 20], etc. Unfortunately, since 3D solution space is much more intricate than that of 2D, these approaches are typically object-centric; also, they mostly focus on generating common

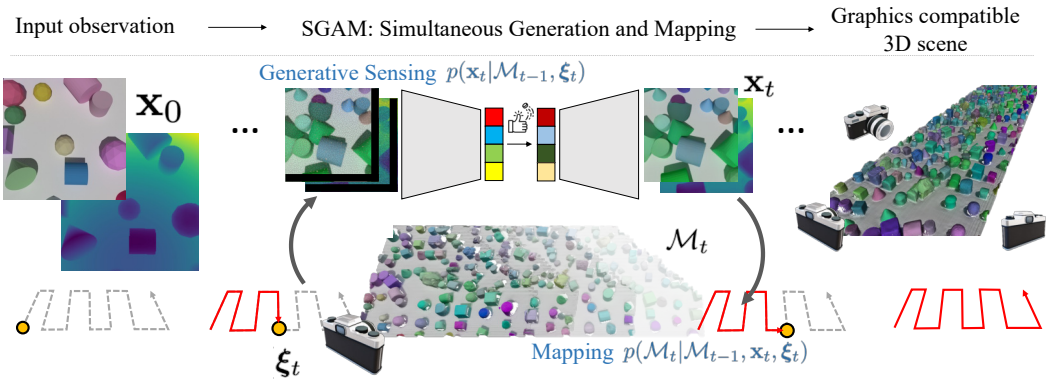


Figure 2: **Overview of our approach.** Our method consists two steps. 1) a generative sensing step $p_\theta(\mathbf{x}_t|\mathcal{M}_{t-1}, \boldsymbol{\xi}_t)$ which renders a realistic and complete sensor observation $\mathbf{x}_t$ given an (incomplete) scene representation $\mathcal{M}_t$ and a query viewpoint $\boldsymbol{\xi}_t$; 2) a mapping module $p_\theta(\mathcal{M}_t|\mathcal{M}_{t-1}, \mathbf{x}_t, \boldsymbol{\xi}_t)$, which integrates the new sensory observation to update the scene. Given an initial snapshot and a camera trajectory, we repeatedly run this generation-mapping process to create the virtual 3D world.

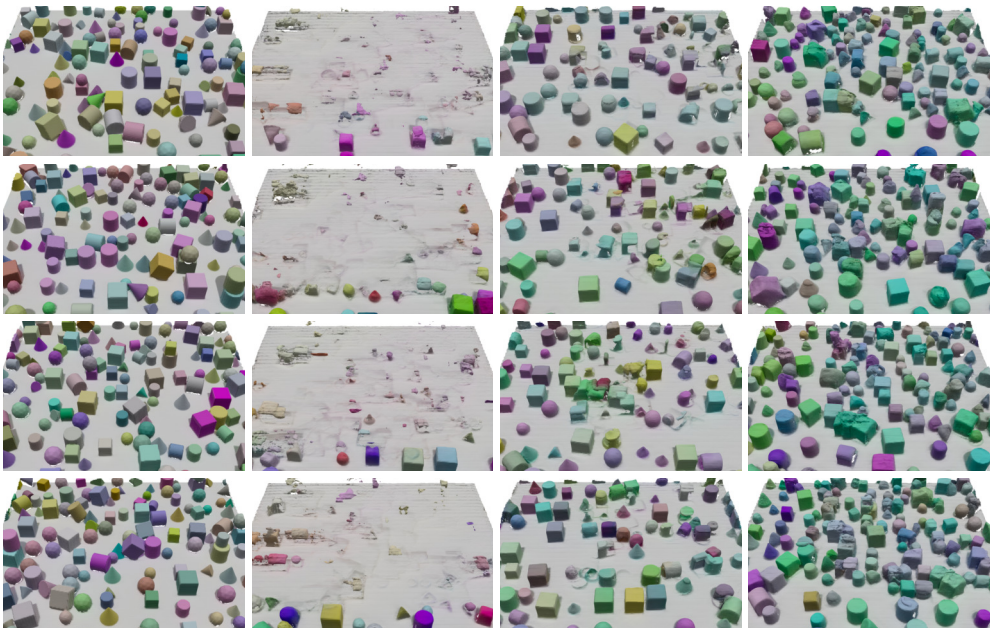
objects in our daily lives [25, 39, 14, 15]. To enable scene-level synthesis, researchers have sought to incorporate more structures into the generation pipeline [47, 54, 51, 53], such as reducing the output space from full 3D to predefined, compact representation [52, 46, 67]. While these strategies greatly alleviate the issue, the generated scene scale is still rather limited (*e.g.*, an indoor environment). In this work, we push the boundary of 3D generation systems and present a model that is capable of generating coherent 3D scene structure over thousands of meters. The produced high-quality 3D world not only allows us to build a large-scale map, but also provides geometric grounding for visual appearance synthesis.

Generative sensor models: Generative sensor models serve critical roles in existing graphics/robotics simulation systems [44, 10]. Their goal is to faithfully simulate the sensor measurement in real world. Depending on the sensor modalities (*e.g.*, rgb/depth cameras, LiDAR scanner), the output can be either photometric or geometric quantities. These methods usually assume an underlying (proxy) 3D geometry is given [80, 59] and then perform conditional generation [43]. The geometry can take various forms (*e.g.*, point clouds [2], surfels [80, 44], meshes [58], etc), as long as it can effectively ground the system. Our full model is a combination of a generative sensor module and a mapping module. The former takes as input RGBD images and simulates both the appearances and the geometry of the scene.

Single image novel view synthesis (NVS): Our work is also related to single image NVS approaches [62, 71, 76, 29], whose goal is to simulate novel views of a scene using only visual cues from one input image. These methods typically rely on neural networks to learn statistical priors from data. Together with carefully designed scene representations (*e.g.*, radiance fields [81, 74], multi-plane images [71], layered depth images [72, 64], etc), they are able to synthesize scene appearance with mild viewpoint change. To push the frontier even further, more recently, researchers have proposed to go beyond local view synthesis, and instead simulate the scene under larger viewpoint change [60, 40, 36, 61, 56]. For instance, generate one room from the other. The task is extremely challenging as it requires the model to learn not only the underlying scene representations, but also the long-range dependencies. Without proper state/map representations, the generated output will easily drift away and the constructed world will no longer be coherent [40, 61]. To address this issue, in this work, we develop a model that simultaneously generates novel views and builds a map. By integrating synthesized results into the map, we are able to query relevant information whenever we re-visit a spot and then decode, allowing us to produce realistic and consistent video footage.

3 SGAM: Simultaneous Generation and Mapping

In this paper, we seek to devise a method that can generate an arbitrarily large, realistic, and consistent *3D world* from *a single snapshot of the scene*. Based on the observation that current 3D scene generation approaches are prone to drifting and often produce inconsistent 3D worlds, we present a novel framework, dubbed as SGAM, that simultaneously generates novel scenes and constructs



GT GFVS-Explicit [61] GFVS-Implicit [61] Ours

Figure 3: **Randomly sampled scenes from CleverInfinite dataset.**

world maps. By grounding the generation and the mapping process in a tightly coupled fashion, we are able to produce a 3D world at a significantly larger scale than any previous 3D generation effort.

We unfold this section by formulating our task in a probabilistic framework. Then we describe how each module can be implemented with a neural network and how we conduct inference to construct the virtual 3D world. Finally, we discuss the learning procedure, our design choices, and the relationships to existing methods.

3.1 Problem Formulation

Given a camera trajectory $\{\boldsymbol{\xi}_t \in \mathbb{SE}(3)\}$ over discrete time steps $\{t\}$ and an initial RGB-D sensor observation $\mathbf{x}_0 \in \mathbb{R}^{W \times H \times 4}$, SGAM aims to compute an estimate of the sensor observation $\mathbf{x}_t \in \mathbb{R}^{W \times H \times 4}$ and a perceived map of the environment $\mathcal{M}_t$ as a set of 3D surface points and associated colors $\{\mathbf{p}_i \in \mathbb{R}^3, \mathbf{c}_i \in \mathbb{R}^3\}_{1 \ldots N_t}$. Due to the inherent randomness, we consider all the quantities to be random variables, so the objective is to model:

$$p(\mathcal{M}_{1 \ldots t}, \mathbf{x}_{1 \ldots t} | \boldsymbol{\xi}_{1 \ldots t}) \tag{1}$$

Using Bayes rule and Markov property, SGAM factors the joint probability into a product of conditional probability over all discrete time steps and concerns the following auto-regressive model at each step t:

$$p(\mathcal{M}_t, \mathbf{x}_t | \mathcal{M}_{t-1}, \boldsymbol{\xi}_t) = p(\mathbf{x}_t | \mathcal{M}_{t-1}, \boldsymbol{\xi}_t) p(\mathcal{M}_t | \mathcal{M}_{t-1}, \mathbf{x}_t, \boldsymbol{\xi}_t) \tag{2}$$

As shown from this equation, at each step SGAM needs to estimate two conditional probabilities: 1) a generative sensor module $p_\theta(\mathbf{x}_t | \mathcal{M}_{t-1}, \boldsymbol{\xi}_t)$ which renders a realistic and complete sensor observation $\mathbf{x}_t$ given an (incomplete) scene representation $\mathcal{M}_t$ and a query viewpoint $\boldsymbol{\xi}_t$; 2) a mapping module $p_\theta(\mathcal{M}_t | \mathcal{M}_{t-1}, \mathbf{x}_t, \boldsymbol{\xi}_t)$, which integrates the new sensory observation to update the scene. Next we will describe each module in detail.

3.2 Generative Sensing

We first describe our generative sensing module $p(\mathbf{x}_t | \mathcal{M}_{t-1}, \boldsymbol{\xi}_t)$, which samples a new RGBD observation $\mathbf{x}_t$ given a query viewpoint $\boldsymbol{\xi}_t$ and the current scene representation. Three desired properties of sensor data generation are 1) *consistency* the generated sensory data is consistent with existing knowledge about the 3D scene; 2) *realism*: the resulting images look realistic, regardless of

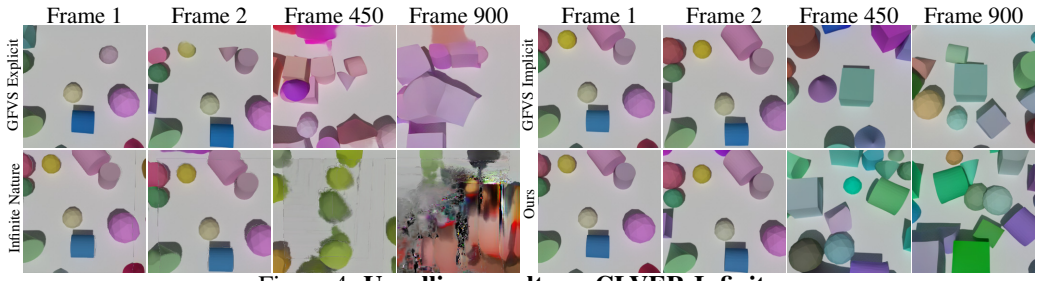


Figure 4: **Unrolling results on CLVER-Infinite.**

Renderer	PSNR↑	SSIM↑	LPIPS↓	ref-FID↓	FID↓	Runtime ↓
InfiniteNature [40]	20.48	0.876	0.247	21.09	28.99	**0.15**
GFVS-implicit [61]	23.06	0.872	0.138	10.47	**20.535**	33.65
GFVS-explicit [61]	18.53	0.812	0.256	15.66	21.55	10.86
Ours	**24.65**	**0.901**	**0.111**	**7.80**	20.90	0.26

Table 1: **Comparison study** of ours and baseline methods on the CLEVR-Infinite validation set. The unit for runtime is average second per image.

how many auto-regressive steps we have run; 3) *completeness*: the sensing module should produce complete observation over both explored and unexplored areas, allowing our scene representation to expand the virtual world as camera moves. Towards these goals, we propose a two steps process including neural rendering and conditional generative refinement as shown in Figure 2.

Scene rendering: We firstly create a guidance image at the target pose by rendering the current scene $\mathbf{x}'_t = \pi(\mathcal{M}_{t-1}, \boldsymbol{\xi}_t)$, where π is an image-based rendering procedure. Given a triangular mesh extracted from the scene representation $\mathcal{M}_{t-1}$, the image-based rendering pipeline first produces a dense depth map at the target pose $\boldsymbol{\xi}_t$ through rasterization. The rendered depth map is then used for inverse warping, producing an RGB image by transferring color appearance from existing sensor observations to the target image. A geometry consistency check will be conducted between each pixel at the rendered target depth and source depth, ensuring the color comes from the same point in 3D. The image-based rendering step gives us an incomplete RGBD observation, where the missing pixels are due to the incompleteness of the current scene representation. Nevertheless, this step promotes the consistency between the generated sensory data and our current knowledge about the scene, built upon the past generated sensory data.

Generative refinement: Next, we will generate the final complete virtual sensor observation $\mathbf{x}_t$ based the on incomplete rendering $\mathbf{x}'_t$. Inspired by the success of the discrete latent variable models [73, 18, 9] in conditional image generation, we propose a lightweight latent VQGAN-based encoder and decoder module to out-painting the missing regions. Specifically, our network is an encoder-decoder framework with discrete latent variables. The incomplete image is fed into an encoder network during inference, which outputs a continuous-valued latent feature map at a resolution 16×16 on CLEVR-Infinite and 32×32 on GoogleEarth-Infinite. For a latent feature on this map $\mathbf{g}_{\text{enc}}$, we could compute the distribution of its corresponding latent code $\mathbf{z}$ through measuring the soft-max similarity to each element in the pre-trained codebook $\mathbf{e}_i$:

$$q(z = i|\mathbf{x}'_t) = \frac{\exp(-d_i/T)}{\sum_j \exp(-d_j/T)}, d_i = \|\mathbf{e}_i - \mathbf{g}_{\text{enc}}(\mathbf{x}'_t)\|_2^2$$

where $q(z = i|\mathbf{x}'_t)$ is the probability of i-th latent code following a K-dimensional categorical distribution; K is the size of the codebook; T is a temperature parameter; and d_i is the quantization error between the feature vector and the codebook element.

Finally, we generate the outpainted sensory output by sampling each latent code from the proposal distribution, create quantized feature map based on the codebook, and feed the quantized feature into the decoder:

$$\mathbf{x}_t = f_{\text{dec}}(\mathbf{g}_{\text{quant}}) \text{ where } \mathbf{g}_{\text{quant}} = \mathbf{e}_j; j \sim q(\mathbf{z}|\mathbf{x}'_t) \tag{3}$$

Besides temperature sampling discussed in this subsection, other diversity sampling procedures such as Nucleus sampling and top-K sampling also work in practice. Compared to prevailing

Model	Image metrics		Scene metrics				
	FID ↓	IS ↓	JSD (10^{-2}) ↓	MMD (10^{-5}) ↓	MinDist ↓	1-NNA ↓	Cov ↑
GFVS-implicit [61]	**16.14**	1.56	0.775	4.510	**0.205**	0.675	0.376
GFVS-explicit [61]	82.82	3.11	10.870	211.500	0.215	0.825	0.122
Ours	26.60	**1.55**	**0.656**	**4.441**	0.221	**0.585**	**0.454**

Table 2: **Scene-level comparison study** on unrolling 30x30 scenes with prior arts on CLEVR-Infinite. For scene-level metrics, we use 3D hist on 15^3 resolution with Cosine distance.

VQGAN-based work for conditional view synthesis, our method does not require comprehensive transformer-based latent code sampling, leading to a significant boost in speed. Furthermore, we find that our conditional generation produces comparable or better performance in perceptual quality.

3.3 Mapping

Representation Maintaining an efficient and flexible scene representation is crucial for high fidelity 3D virtual world generation at a large scale. Inspired by its success in depth-based SLAM [48] and 3D reconstruction [83], we leverage hashing based volumetric representation [50] for representing $\mathcal{M}_t$. Each voxel $\mathbf{p}$ in the space maintains a signed distance value $\mathcal{M}_t(\mathbf{p}) : \mathbb{R}^3 \to \mathbb{R}$, where the magnitude encodes the distance to the surface boundary, and the sign represents whether it is interior or exterior. Such representation is flexible, allowing us to update online at each step when new sensory data is generated. Additionally, the voxel-hashing structure enables sparse storage, allowing the map to scale to huge scenes.

Integration At each time t, given a new sensor observation $\mathbf{x}_t$, we update our map $\mathcal{M}_t$ following KinectFusion [48]. Specifically, for each value, a weighted sum update is conducted for points along the camera ray:

$$\mathcal{M}_t(\mathbf{p}) = \frac{w_{t-1}(\mathbf{p})\mathcal{M}_t(\mathbf{p}) + O(\mathbf{x}_t, \mathbf{p})}{w_{t-1}(\mathbf{p}) + 1}; w_t(\mathbf{p}) = w_{t-1}(\mathbf{p}) + 1$$

where $O(\mathbf{x}_t, \mathbf{p})$ is the observed signed distance function at $\mathbf{p}$, calculated by the new sensor observation $O(\mathbf{x}_t, \mathbf{p})$; w_t is a counter that summarizes how many steps that $\mathbf{p}$ has been updated. After each integration step, we will also conduct marching cube [41] to extract triangular mesh, allowing us to render images from a new viewpoint during the generative sensing process.

3.4 Learning

SGAM adopts a two-stage training pipeline. In the first stage, inspired by VQGAN [18], we first pre-trained an discrete-latent encoder, decoder and codebook on the clean rgbd image dataset in an auto-encoding fashion. Following the practice in GFVS [61], we use L_1 reconstruction loss, perceptual loss [82], patch-gan-based discriminator loss [30] and commitment loss [18].

Our second stage aims to train the encoder so that it learns to complete the latent code space. Specifically, we fine-tune the encoder with incomplete/complete image pairs. The incomplete RGB-D images are simulated through inverse warping from neighboring viewpoints. We use perceptual loss [82] and patch-gan-based discriminator loss [30] at this stage. In this stage, we freeze the codebook and decoder parameters. We find this mechanism helps maintain the output images realistic even after many unrolling steps during inference.

We use Adam to train our entire network. Learning through a non-differentiable quantization step is hard. To stabilize training, we first train the encoder-decoder network without quantization for the first 30k iterations and then add it back and train the entire network for another 60k iterations using the straight-through gradient estimator trick [3] to back-propagate gradient.

4 Experiments

We first evaluate the effectiveness of SGAM on a large-scale synthetic dataset. Next, we comprehensively study the characteristics of our method. Finally we showcase how SGAM can be applied in real-world scenarios to generate high-quality 3D worlds.

Ground-truth InfiniteNature [40] GFVS-Explicit [61] GFVS-Implicit [61] Ours

Figure 5: **Qualitative result of one-step predictions on CLEVR-Infinite.** Shaded areas are visible regions in source views based on forward warping.

4.1 Setup

Dataset: SGAM requires a myriad of RGB-D images to train. Unfortunately, existing static, large-scale 3D datasets, such as ACID [40] and RealEstate10K [84], do not provide accurate depth. We thus exploit Blender and the assets from CLEVR [31] to render an extremely large-scale synthetic benchmark, which we called CLEVR-Infinite. CLEVR-Infinite contains 72 training scenes and 8 test scenes. For each scene, we sampled a fixed number of objects from the asset bank with replacement and randomly placed them on the ground plane. The asset bank consists of four primitive shapes, each of which with three different scales. We set all object material to diffuse, and determine their color randomly. We use the same environmental light across all scenes. The cameras are distributed uniformly among the 50×50 grid plane right above and parallel to the ground. We set the pitch (*i.e.*, the angle between the look-at vector and the plane) of the cameras to be $80°$. In total, the dataset contains 200k RGB-D images at the resolution of 256×256.

Metrics: We evaluate the generated 3D world both *locally at the image level* and *globally at the scene level*. The former measures to what degree the synthetic scene reproduces the local details, while the latter quantifies how well the virtual world matches the statistics of the original counterpart.

Following previous work [45, 81], we first use Peak Signal-to-Noise Ratio (PSNR), Structural Similarity (SSIM), and LPIPS [82] to measure the image level similarity with respect to the GT. However, since our model is generative, we might synthesize scenes that are plausible yet different from the original one. We thus further employ Fréchet inception distance (FID) [27] to measure the generative quality. Specifically, two FID score are reported: (i) ref-FID, which we compare against the GT; and (ii) FID, which we compare against a separate set of images from test set.

As for scene-level evaluation, we follow prior art in 3D generative models [1, 79] to gauge the overall geometry quality with a diverse set of metrics: Jensen-Shannon divergence (JSD), maximum mean discrepancy (MMD), coverage (COV), minimum matching distance (MinDist), and 1-nearest neighbor accuracy (1-NNA). Specifically, we first divide the whole scene into non-overlapping regions. Each region is then discretized into 15^3 voxels. Finally, we compute the 3D histogram within each local grid and employ cosine distance to compute the metrics. To ensure the generated scene as a whole looks realistic, we also compute the Inception Score (IS) and FID against random sampled scenes from the test set.

Lastly, to demonstrate the efficiency of our method, we report the runtime of a single prediction step. The numbers are benchmarked on Nvidia Quadro 8000. We sample the latent code that is closest to image features during one-step and scene-level prediction for our method.

Baselines: We compare SGAM against state-of-the-art approaches in long range scene generation: GFVS [61] and InfiniteNature [40]. For GFVS, we consider both the explicit-image and implicit-depth variants with the following modifications: first, we use a single codebook to encode RGB-D rather than two, which better combines texture and geometry during scene expansion; second, to support multi-image input, we conduct average pooling over the features of source images before

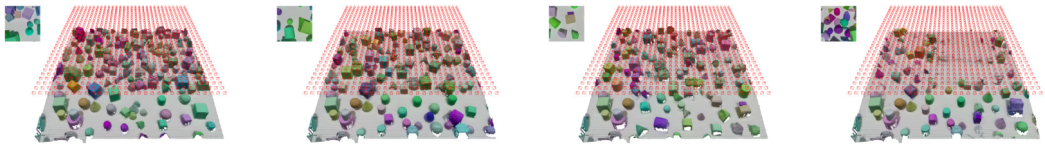


Figure 6: **Diversity samples of the 3D scene using different virtual camera trajectories.**

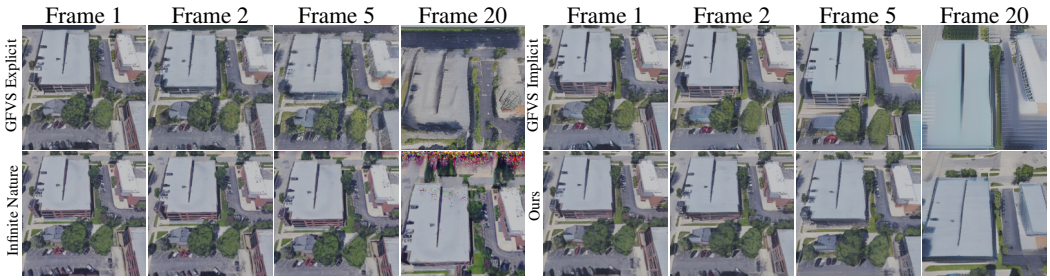


Figure 7: **Unrolling results on Google-Earth.**

passing it to an MLP to infer the target code. For InfiniteNature, since the authors did not release their training scripts, we re-implement their method in Pytorch. We remove the geometric grounding step since we find it harmful when we unroll the scene in CLEVR-Infinite.

Implementation details: During full scene evaluation, we generate the scene in a zig-zag fashion on a 30×30 grid. We start from coordinate (0, 0) and unroll for 900 steps. The above procedure is repeated for 10 times with different seed images. For a fair comparison, GFVS-implicit, GFVS-explicit and SGAM share the same codebook embedding and the same weights for decoder. We set the vocabulary size to 16384. We implement SGAM in PyTorch, and train with a batch size of 8 on 2 Nvidia A40 GPU until convergence. For other baselines, we maximize batch size to fit GPU memory, and train until convergence. During the first-stage codebook training, we follow the exact training config as GFVS first-stage training in the official codebase. GFVS-implicit, GFVS-explicit and SGAM share the same learning rate at 0.0625 for the second-stage trainig.

4.2 Experimental results

As shown in Tab. 1, SGAM achieves superior or comparable performance across all image level metrics. Comparing to the second best approach, GFVS-Implicit, we are much more efficient. We use less CPU and GPU memory and our runtime is 150 times faster. Fig. 5 shows a few one step prediction results. SGAM is able to faithfully reconstruct the color and the shape of the assets within the visible area, and generate the invisible region in a coherent, harmonic fashion. When unrolling multiple steps (see. Fig. 4 and Tab. 2), baselines such as InfiniteNature and GFVS-explicit suffer from error accumulation, and collapse catastrophically. GFVS-implicit generates objects that resemble the GT data, yet it sacrifices the speed and fails to enforce consistency across frames (see Fig. 5). Our approach, in contrast, is able to produce consistent and realistic results in an efficient manner.

Color bias: One limitation of SGAM is that it tends to favor green over other colors during the generation process. We conjecture that the color bias originates from the environmental map we used during rendering. The illumination color difference affects the visual features and thereby bias the sampling towards code word that are more green. We leave this for future study.

4.3 Analysis

Importance of two-stage training: Two-stage training is critical. Removing either stage degrades our performance. Without the first-stage codebook training, the generative sensing module will have to learn the codebook from warped inputs, which could inevitably encode missing holes into the codebook. On the other hand, by finetuning the encoder from a converged first-stage checkpoint, we consistently improve the performance of our model across all image level metrics. Specifically, we

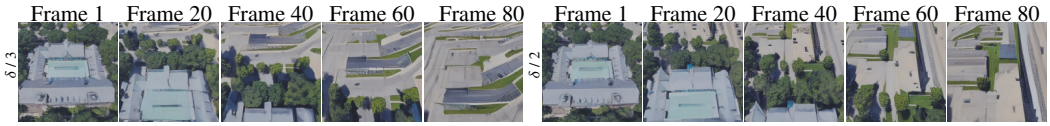


Figure 8: **Diversity samples of the 3D scene using different step size.** δ refers to the distance between neighboring camera centers in the dataset. The left frames use one third of the unit distance, while the right uses one half

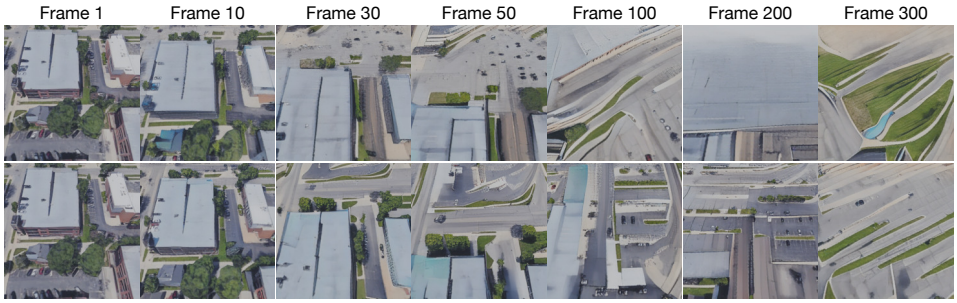


Figure 9: **Ablation Study on the effect of RGBD-integration** to SGAM on GoogleEarth-infinite dataset. The first row is one without RGBD-integration per-step, and the second row is with RGBD-integration. All methods share the same seed image, Frame 0.

increase PSNR by 29.6 % and SSIM by 13.8 %; we also reduce LPIPS by 59.3 %, ref-FID by 72.8 %, and FID by 6.6 %. We refer the readers to the supp. materials for detailed numbers.

Real-world scene: We also apply SGAM and the baselines to real-world images that we scraped from Google Earth (see Fig. 7). Similar as before, both InfiniteNature and GFVS-explicit suffer from severe domain shift. Since the images contain more diverse and complicated scene structures, GFVS-implicit fails to capture the viewpoint shift precisely during unrolling. In contrast, SGAM can produce consistent and realistic results. Please refer to supp. material for more details on the data.

Diversity: SGAM allows us to create diverse 3D world by varying camera trajectories and by varying the step size. As shown in Fig. 6 and Fig. 8, both of which are very effective. `Greedy` samples the next target pose based on the L1 distance of the visible region of the warped views.

Effectiveness of RGB-D integration: When color point cloud is used as global scene representation, the more nearby source views to sample, the more complete $\mathcal{M}_{t-1}$ is, but the noisier $\mathcal{M}_{t-1}$ becomes, which hurdles inference quality at the generative refinement stage. To denoise the mapping $\mathcal{M}_{t-1}$, we find it effective to refine and grow the global scene with RGBD-integrated 3D mesh using KinectFusion [48]. We demonstrate in Fig. 9 that RGBD-integration denoised mapping can achieve much more diverse scenarios than the one without, which scene degrades to large empty airport ground around 200 steps of unrolling becomes it unable to fit latent code to fit noisy features.

Limitations: Our experiments demonstrate that our model can synthesize consistent, realistic, and large-scale real-world data given only the initial observation of the scene. However, we do notice that we also need further to boost the diversity of SGAM on the GoogleEarth dataset. After unrolling hundreds of steps, SGAM likely converges to generate street scenes rather than a variety of scenarios, such as parks, golf fields, commercial zones, etc. We conjecture that this is either due to 1) the dataset bias, 2) hyper-parameters of our temperature sampling, or 3) biases in the pretrained codebook.

Societal impact: Realistic 3D generation technology has many applications, such as visual content creation and simulation. Unfortunately, it may also be used to spread misinformation.

5 Conclusion

In this paper, we present a novel 3D scene generation algorithm, SGAM, which create a consistent, realistic, and large-scale 3D virtual world through simultaneous generation and mapping. Our result demonstrates we can achieve similar (in synthetic data) or even more realistic (in real-world data) sensor observation than methods with Transformer-based latent code sampler during unrolling.

References

[1] Panos Achlioptas, Olga Diamanti, Ioannis Mitliagkas, and Leonidas Guibas. Learning representations and generative models for 3d point clouds. In *ICML*, 2018.

[2] Kara-Ali Aliev, Artem Sevastopolsky, Maria Kolos, Dmitry Ulyanov, and Victor Lempitsky. Neural point-based graphics. 2020.

[3] Yoshua Bengio, Nicholas Léonard, and Aaron Courville. Estimating or propagating gradients through stochastic neurons for conditional computation. *arXiv preprint arXiv:1308.3432*, 2013.

[4] James R Bergen and Edward H Adelson. Early vision and texture perception. *Nature*, 1988.

[5] Filip Biljecki, Jantien Stoter, Hugo Ledoux, Sisi Zlatanova, and Arzu Çöltekin. Applications of 3d city models: State of the art review. *ISPRS International Journal of Geo-Information*, 4(4):2842–2889, 2015.

[6] Volker Blanz and Thomas Vetter. A morphable model for the synthesis of 3d faces. In *SIGGRAPH*, 1999.

[7] Lucas Caccia, Herke Van Hoof, Aaron Courville, and Joelle Pineau. Deep generative modeling of lidar data. In *IROS*, 2019.

[8] Wayne E Carlson. An algorithm and data structure for 3d object synthesis using surface patch intersections. In *SIGGRAPH*, 1982.

[9] Huiwen Chang, Han Zhang, Lu Jiang, Ce Liu, and William T Freeman. Maskgit: Masked generative image transformer. *arXiv*, 2022.

[10] Yun Chen, Frieda Rong, Shivam Duggal, Shenlong Wang, Xinchen Yan, Sivabalan Manivasagam, Shangjie Xue, Ersin Yumer, and Raquel Urtasun. Geosim: Realistic video simulation via geometry-aware composition for self-driving. In *CVPR*, 2021.

[11] Yen-Chi Cheng, Chieh Hubert Lin, Hsin-Ying Lee, Jian Ren, Sergey Tulyakov, and Ming-Hsuan Yang. In&out: Diverse image outpainting via gan inversion. *arXiv*, 2021.

[12] Blender Online Community. *Blender - a 3D modelling and rendering package*. Blender Foundation, Stichting Blender Foundation, Amsterdam, 2018.

[13] Alexey Dosovitskiy, German Ros, Felipe Codevilla, Antonio Lopez, and Vladlen Koltun. CARLA: An open urban driving simulator. In *Proceedings of the 1st Annual Conference on Robot Learning*, pages 1–16, 2017.

[14] Shivam Duggal and Deepak Pathak. Topologically-aware deformation fields for single-view 3d reconstruction. *CVPR*, 2022.

[15] Shivam Duggal, Zihao Wang, Wei-Chiu Ma, Sivabalan Manivasagam, Justin Liang, Shenlong Wang, and Raquel Urtasun. Mending neural implicit modeling for 3d vehicle reconstruction in the wild. In *WACV*, 2022.

[16] Alexei A Efros and William T Freeman. Image quilting for texture synthesis and transfer. In *Proceedings of the 28th annual conference on Computer graphics and interactive techniques*, 2001.

[17] Alexei A Efros and Thomas K Leung. Texture synthesis by non-parametric sampling. In *ICCV*, 1999.

[18] Patrick Esser, Robin Rombach, and Björn Ommer. Taming transformers for high-resolution image synthesis. In *CVPR*, 2021.

[19] Rohit Girdhar, David F Fouhey, Mikel Rodriguez, and Abhinav Gupta. Learning a predictable and generative vector representation for objects. In *ECCV*, 2016.

[20] Georgia Gkioxari, Jitendra Malik, and Justin Johnson. Mesh r-cnn. In *ICCV*, 2019.

[21] Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial networks, 2014.

[22] Arthur Gretton, Karsten Borgwardt, Malte J Rasch, Bernhard Scholkopf, and Alexander J Smola. A kernel method for the two-sample problem. *arXiv preprint arXiv:0805.2368*, 2008.

[23] Giorgio Grisetti, Rainer Kümmerle, Cyrill Stachniss, and Wolfram Burgard. A tutorial on graph-based slam. *IEEE Intelligent Transportation Systems Magazine*, 2(4):31–43, 2010.

[24] Thibault Groueix, Matthew Fisher, Vladimir G Kim, Bryan C Russell, and Mathieu Aubry. A papier-mâché approach to learning 3d surface generation. In *CVPR*, 2018.

[25] Jiayuan Gu, Wei-Chiu Ma, Sivabalan Manivasagam, Wenyuan Zeng, Zihao Wang, Yuwen Xiong, Hao Su, and Raquel Urtasun. Weakly-supervised 3d shape completion in the wild. In *ECCV*, 2020.

[26] David J Heeger and James R Bergen. Pyramid-based texture analysis/synthesis. In *Proceedings of the 22nd annual conference on Computer graphics and interactive techniques*, 1995.

[27] Martin Heusel, Hubert Ramsauer, Thomas Unterthiner, Bernhard Nessler, and Sepp Hochreiter. Gans trained by a two time-scale update rule converge to a local nash equilibrium. *NeurIPS*, 2017.

[28] Jonathan Ho, Ajay Jain, and Pieter Abbeel. Denoising diffusion probabilistic models. *NeurIPS*, 2020.

[29] Ronghang Hu, Nikhila Ravi, Alex Berg, and Deepak Pathak. Worldsheet: Wrapping the world in a 3d sheet for view synthesis from a single image. *ICCV*, 2021.

[30] Phillip Isola, Jun-Yan Zhu, Tinghui Zhou, and Alexei A Efros. Image-to-image translation with conditional adversarial networks. In *CVPR*, 2017.

[31] Justin Johnson, Bharath Hariharan, Laurens van der Maaten, Li Fei-Fei, C Lawrence Zitnick, and Ross Girshick. Clevr: A diagnostic dataset for compositional language and elementary visual reasoning. In *CVPR*, 2017.

[32] B. Julesz. Visual pattern discrimination. *IRE Transactions on Information Theory*, 1962.
[33] Tero Karras, Timo Aila, Samuli Laine, and Jaakko Lehtinen. Progressive growing of gans for improved quality, stability, and variation. *arXiv*, 2017.
[34] Tero Karras, Samuli Laine, and Timo Aila. A style-based generator architecture for generative adversarial networks. In *CVPR*, 2019.
[35] Diederik P Kingma and Max Welling. Auto-encoding variational bayes. *arXiv*, 2013.
[36] Jing Yu Koh, Honglak Lee, Yinfei Yang, Jason Baldridge, and Peter Anderson. Pathdreamer: A world model for indoor navigation. 2021.
[37] Chieh Hubert Lin, Yen-Chi Cheng, Hsin-Ying Lee, Sergey Tulyakov, and Ming-Hsuan Yang. InfinityGAN: Towards infinite-pixel image synthesis. In *ICLR*, 2022.
[38] Chen-Hsuan Lin, Chen Kong, and Simon Lucey. Learning efficient point cloud generation for dense 3d object reconstruction. In *AAAI*, 2018.
[39] Chen-Hsuan Lin, Chaoyang Wang, and Simon Lucey. Sdf-srn: Learning signed distance 3d object reconstruction from static images. *NeurIPS*, 2020.
[40] Andrew Liu, Richard Tucker, Varun Jampani, Ameesh Makadia, Noah Snavely, and Angjoo Kanazawa. Infinite nature: Perpetual view generation of natural scenes from a single image. In *ICCV*, 2021.
[41] William E. Lorensen and Harvey E. Cline. Marching cubes: A high resolution 3d surface construction algorithm. In *Proceedings of the 14th Annual Conference on Computer Graphics and Interactive Techniques*, SIGGRAPH '87, page 163–169, New York, NY, USA, 1987. Association for Computing Machinery.
[42] Jitendra Malik and Pietro Perona. Preattentive texture discrimination with early vision mechanisms. (5), 1990.
[43] Arun Mallya, Ting-Chun Wang, Karan Sapra, and Ming-Yu Liu. World-consistent video-to-video synthesis. In *ECCV*, 2020.
[44] Sivabalan Manivasagam, Shenlong Wang, Kelvin Wong, Wenyuan Zeng, Mikita Sazanovich, Shuhan Tan, Bin Yang, Wei-Chiu Ma, and Raquel Urtasun. Lidarsim: Realistic lidar simulation by leveraging the real world. In *CVPR*, 2020.
[45] Ben Mildenhall, Pratul P Srinivasan, Matthew Tancik, Jonathan T Barron, Ravi Ramamoorthi, and Ren Ng. Nerf: Representing scenes as neural radiance fields for view synthesis. In *ECCV*, 2020.
[46] Nelson Nauata, Kai-Hung Chang, Chin-Yi Cheng, Greg Mori, and Yasutaka Furukawa. House-gan: Relational generative adversarial networks for graph-constrained house layout generation. In *ECCV*, 2020.
[47] Nelson Nauata, Sepidehsadat Hosseini, Kai-Hung Chang, Hang Chu, Chin-Yi Cheng, and Yasutaka Furukawa. House-gan++: Generative adversarial layout refinement networks. *arXiv*, 2021.
[48] Richard A. Newcombe, Shahram Izadi, Otmar Hilliges, David Molyneaux, David Kim, Andrew J. Davison, Pushmeet Kohi, Jamie Shotton, Steve Hodges, and Andrew Fitzgibbon. Kinectfusion: Real-time dense surface mapping and tracking. In *2011 10th IEEE International Symposium on Mixed and Augmented Reality*, pages 127–136, 2011.
[49] Thu Nguyen-Phuoc, Chuan Li, Lucas Theis, Christian Richardt, and Yong-Liang Yang. Hologan: Unsupervised learning of 3d representations from natural images. In *ICCV*, 2019.
[50] Matthias Nießner, Michael Zollhöfer, Shahram Izadi, and Marc Stamminger. Real-time 3d reconstruction at scale using voxel hashing. *ACM Transactions on Graphics (ToG)*, 32(6):1–11, 2013.
[51] Despoina Paschalidou, Amlan Kar, Maria Shugrina, Karsten Kreis, Andreas Geiger, and Sanja Fidler. Atiss: Autoregressive transformers for indoor scene synthesis. In *NeurIPS*, 2021.
[52] Chi-Han Peng, Yong-Liang Yang, and Peter Wonka. Computing layouts with deformable templates. *TOG*, 2014.
[53] Shengyi Qian, Alexander Kirillov, Nikhila Ravi, Devendra Singh Chaplot, Justin Johnson, David F Fouhey, and Georgia Gkioxari. Recognizing scenes from novel viewpoints. *arXiv*, 2021.
[54] Yiming Qian, Hao Zhang, and Yasutaka Furukawa. Roof-gan: learning to generate roof geometry and relations for residential houses. In *CVPR*, 2021.
[55] Alec Radford, Luke Metz, and Soumith Chintala. Unsupervised representation learning with deep convolutional generative adversarial networks. *arXiv*, 2015.
[56] Xuanchi Ren and Xiaolong Wang. Look outside the room: Synthesizing a consistent long-term 3d scene video from a single image. In *CVPR*, 2022.
[57] Danilo Rezende and Shakir Mohamed. Variational inference with normalizing flows. In *ICML*, 2015.
[58] Gernot Riegler and Vladlen Koltun. Free view synthesis. In *European Conference on Computer Vision*, 2020.
[59] Gernot Riegler and Vladlen Koltun. Stable view synthesis. In *CVPR*, 2021.
[60] Chris Rockwell, David F. Fouhey, and Justin Johnson. Pixelsynth: Generating a 3d-consistent experience from a single image. In *ICCV*, 2021.
[61] Robin Rombach, Patrick Esser, and Björn Ommer. Geometry-free view synthesis: Transformers and no 3d priors. In *ICCV*, 2021.
[62] Bryan C. Russell and Antonio Torralba. Building a database of 3d scenes from user annotations. In *CVPR*, 2009.

[63] Tim Salimans, Ian Goodfellow, Wojciech Zaremba, Vicki Cheung, Alec Radford, and Xi Chen. Improved techniques for training gans. *Advances in neural information processing systems*, 29, 2016.

[64] Meng-Li Shih, Shih-Yang Su, Johannes Kopf, and Jia-Bin Huang. 3d photography using context-aware layered depth inpainting. In *CVPR*, 2020.

[65] Ruben M Smelik, Tim Tutenel, Rafael Bidarra, and Bedrich Benes. A survey on procedural modelling for virtual worlds. In *Computer Graphics Forum*, volume 33, pages 31–50. Wiley Online Library, 2014.

[66] Yang Song, Jascha Sohl-Dickstein, Diederik P Kingma, Abhishek Kumar, Stefano Ermon, and Ben Poole. Score-based generative modeling through stochastic differential equations. *arXiv*, 2020.

[67] Shuhan Tan, Kelvin Wong, Shenlong Wang, Sivabalan Manivasagam, Mengye Ren, and Raquel Urtasun. Scenegen: Learning to generate realistic traffic scenes. In *CVPR*, 2021.

[68] Johan WH Tangelder and Remco C Veltkamp. A survey of content based 3d shape retrieval methods. *Multimedia tools and applications*, 2008.

[69] Maxim Tatarchenko, Stephan R Richter, René Ranftl, Zhuwen Li, Vladlen Koltun, and Thomas Brox. What do single-view 3d reconstruction networks learn? In *CVPR*, 2019.

[70] Piotr Teterwak, Aaron Sarna, Dilip Krishnan, Aaron Maschinot, David Belanger, Ce Liu, and William T Freeman. Boundless: Generative adversarial networks for image extension. In *ICCV*, 2019.

[71] Richard Tucker and Noah Snavely. Single-view view synthesis with multiplane images. In *CVPR*, 2020.

[72] Shubham Tulsiani, Richard Tucker, and Noah Snavely. Layer-structured 3d scene inference via view synthesis. In *ECCV*, 2018.

[73] Aaron Van Den Oord, Oriol Vinyals, et al. Neural discrete representation learning. *NeurIPS*, 2017.

[74] Qianqian Wang, Zhicheng Wang, Kyle Genova, Pratul P Srinivasan, Howard Zhou, Jonathan T Barron, Ricardo Martin-Brualla, Noah Snavely, and Thomas Funkhouser. Ibrnet: Learning multi-view image-based rendering. In *CVPE*, 2021.

[75] Zhou Wang, Alan C Bovik, Hamid R Sheikh, and Eero P Simoncelli. Image quality assessment: from error visibility to structural similarity. *IEEE transactions on image processing*, 13(4):600–612, 2004.

[76] Olivia Wiles, Georgia Gkioxari, Richard Szeliski, and Justin Johnson. Synsin: End-to-end view synthesis from a single image. In *CVPR*, 2020.

[77] Jiajun Wu, Yifan Wang, Tianfan Xue, Xingyuan Sun, Bill Freeman, and Josh Tenenbaum. Marrnet: 3d shape reconstruction via 2.5 d sketches. *NeurIPS*, 2017.

[78] Jiajun Wu, Chengkai Zhang, Tianfan Xue, Bill Freeman, and Josh Tenenbaum. Learning a probabilistic latent space of object shapes via 3d generative-adversarial modeling. *NeurIPS*, 2016.

[79] Guandao Yang, Xun Huang, Zekun Hao, Ming-Yu Liu, Serge Belongie, and Bharath Hariharan. Pointflow: 3d point cloud generation with continuous normalizing flows. In *ICCV*, 2019.

[80] Zhenpei Yang, Yuning Chai, Dragomir Anguelov, Yin Zhou, Pei Sun, Dumitru Erhan, Sean Rafferty, and Henrik Kretzschmar. Surfelgan: Synthesizing realistic sensor data for autonomous driving. In *CVPR*, 2020.

[81] Alex Yu, Vickie Ye, Matthew Tancik, and Angjoo Kanazawa. pixelNeRF: Neural radiance fields from one or few images. In *CVPR*, 2021.

[82] Richard Zhang, Phillip Isola, Alexei A Efros, Eli Shechtman, and Oliver Wang. The unreasonable effectiveness of deep features as a perceptual metric. In *CVPR*, 2018.

[83] Qian-Yi Zhou, Stephen Miller, and Vladlen Koltun. Elastic fragments for dense scene reconstruction. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 473–480, 2013.

[84] Tinghui Zhou, Richard Tucker, John Flynn, Graham Fyffe, and Noah Snavely. Stereo magnification: Learning view synthesis using multiplane images. *arXiv*, 2018.

[85] Song Chun Zhu, Yingnian Wu, and David Mumford. Filters, random fields and maximum entropy (frame): Towards a unified theory for texture modeling. *International Journal of Computer Vision*, 1998.

Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes]
   (c) Did you discuss any potential negative societal impacts of your work? [Yes] Please see supp. material for the discussion.
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [N/A]

(b) Did you include complete proofs of all theoretical results? [N/A]

3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [No] We plan to release the code after acceptance.
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] Our SGAM is built on top of VQGAN codebase. We re-use the hyperparameters among all baselines.
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? We randomly generate multiple scene with different seed images, i.e., initiall sensor observation to capture overall model performance. [N/A]
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes]
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5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]
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