RODIN: A Generative Model for Sculpting 3D Digital Avatars Using Diffusion

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Figure 1. Our diffusion model, RODIN, can produce high-fidelity 3D avatars (the first row). Our model also supports 3D avatar generation from a single portrait or text prompt, while permitting text-based semantic manipulation (second row). See the webpage for video demos.

Abstract

This paper presents a 3D diffusion model that automatically generates 3D digital avatars represented as neural radiance fields (NeRFs). A significant challenge for 3D diffusion is that the memory and processing costs are prohibitive for producing high-quality results with rich details. To tackle this problem, we propose the roll-out diffusion network (RODIN), which takes a 3D NeRF model represented as multiple 2D feature maps and rolls out them onto a single 2D feature plane within which we perform 3D-aware diffusion. The RODIN model brings much-needed computational efficiency while preserving the integrity of 3D diffusion by using 3D-aware convolution that attends to projected features in the 2D plane according to their original relationships in 3D. We also use latent conditioning to orchestrate the feature generation with global coherence, leading to high-fidelity avatars and enabling semantic editing based on text prompts. Finally, we use hierarchical synthesis to further enhance details. The 3D avatars generated by our model compare favorably with those produced by existing techniques. We can generate highly detailed avatars with realistic hairstyles and facial hair. We also demonstrate 3D avatar generation from image or text, as well as text-guided editability.

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1. Introduction

Generative models [2, 34] are one of the most promising ways to analyze and synthesize visual data including 2D images and 3D models. At the forefront of generative modeling is the diffusion model [14, 24, 61], which has shown phenomenal generative power for images [19,47,50,52] and videos [23,59]. Indeed, we are witnessing a 2D content creation revolution driven by the rapid advances of diffusion and generative modeling. In this paper, we aim to expand the applicability of diffusion to 3D digital avatars. We use "digital avatars" to refer to the traditional avatars manually created by 3D artists, as opposed to the recently emerging photorealistic avatars [8, 43]. The reason for focusing on digital avatars is twofold. On the one hand, digital avatars are widely used in movies, games, the metaverse, and the 3D industry in general. On the other hand, the available digital avatar data is very scarce as each avatar must be painstakingly created by a specialized 3D artist using a sophisticated creation pipeline [20, 35], especially for modeling hair and facial hair. All this leads to a compelling scenario for generative modeling.

We present a diffusion model for automatically producing digital avatars represented as NeRFs [38], with each point describing its color radiance and density within the 3D volume. The core challenge in generating these avatars

is the prohibitive memory and computational cost required by high-quality avatars with rich details. Without rich details, an avatar will always be somewhat "toy-like". To tackle this challenge, we develop RODIN, the roll-out diffusion network. We take a NeRF model represented as multiple 2D feature maps and roll out these maps onto a single 2D feature plane and perform 3D-aware diffusion within this plane. Specifically, we use the tri-plane representation [9], which represents a volume by three orthogonal feature planes. By simply rolling out the feature maps, RODIN can perform 3D-aware diffusion using an efficient 2D architecture and by drawing power from RODIN's three key ingredients.

The first is the 3D-aware convolution. The 2D CNN processing used in conventional 2D diffusion cannot effectively handle feature maps originating from orthogonal planes. Rather than treating the features as plain 2D input, the 3D-aware convolution explicitly accounts for the fact that a 2D feature in one plane (of the tri-plane) is a projection from a piece of 3D data and is hence intrinsically associated with the same data's projected features in the other two planes. To encourage cross-plane communication, we involve all these associated features in the convolution and synchronize their detail synthesis according to their 3D relationship.

The second ingredient is latent conditioning. We use a latent vector to orchestrate the feature generation so that it is globally coherent in 3D, leading to better quality avatars and enabling semantic editing. We do this by using the avatars in the training dataset to train an additional image encoder which extracts a semantic latent vector serving as the conditional input to the diffusion model. This latent conditioning essentially acts as an autoencoder in orchestrating the feature generation. For semantic editability, we adopt a frozen CLIP image encoder [46] that shares the latent space with text prompts.

The final ingredient is hierarchical synthesis. We start by generating at low resolution (64×64), followed by a diffusion-based upsampling that yields a higher resolution (256×256). When training the diffusion upsampler, it is instrumental to penalize the image-level loss that we compute in a patch-wise manner.

RODIN supports several application scenarios. We can use the model to generate an unlimited number of avatars from scratch, each different from the others as well as those in the training data. As shown in Figure 1, we can generate highly detailed avatars with realistic hairstyles and facial hair styled as beards, mustaches, goatees, and sideburns. Hairstyle and facial hair are essential parts of personal identity yet have been notoriously difficult to model well with existing approaches. The RODIN model also allows avatar customization, with the resulting avatar capturing the visual characteristics of a person portrayed in an image or a textual description. Finally, our framework supports text-guided semantic editing.

Our work shows that 3D diffusion holds great modeling power, and this power can be effectively unleashed by rolling out the feature maps onto a 2D plane, leading to rich details, including those highly desirable but extremely difficult to produce with existing techniques. It is worth noting that while this paper focuses on RODIN's application to avatars, the design of RODIN is not avatar specific. Indeed, we believe RODIN is applicable to general 3D scenes.

2. Related Work

The state of generative modeling [5, 14, 15, 28, 48, 65, 75] has seen rapid progress in past years. Diffusion models [14, 24, 61, 73] have recently shown unprecedented generative ability and compositional power. The most remarkable success happens in text-to-image synthesis [19, 39, 47, 50, 52], which serves as a foundation model and enables various appealing applications [21, 51, 66] previously unattainable. While diffusion models have been successfully applied to different modalities [11, 23, 26, 32], its generative capability is much less explored in 3D generation, with only a few attempts on modeling 3D primitives [36, 74, 76].

Early 3D generation works rely on either GAN [17] or VAE [29] to model the distribution of 3D shape representation like voxel grids [6, 70], point clouds [1, 7, 31, 72], mesh [33, 63] and implicit neural representation [42, 60]. However, existing works have not demonstrated the ability to produce complex 3D assets yet. Concurrent to this work, Bautista *et al*. [4] train a diffusion model to generate the latent vector that encodes the radiance field [38] of synthetic scenes, yet this work only produces coarse 3D geometry. In comparison, we propose a hierarchical 3D generation framework with effective 3D-aware operators, offering unprecedented 3D detail synthesis.

Another line of work learns 3D-aware generation by utilizing richly available 2D data. 3D-aware GANs [9, 10, 12, 16, 18, 41, 54–58, 62, 71, 77] recently attract significant research interest, which are trained to produce radiance fields with image level distribution matching. However, these methods suffer from instabilities and mode collapse of GAN training, and it is still challenging to attain authentic avatars that can be viewed from large angles. Concurrently, there are a few attempts to use diffusion models for the problem. Daniel *et al*. [68] proposes to synthesize novel views with a pose-conditioned 2D diffusion model, yet the results are not intrinsically 3D. Ben *et al*. [45] optimizes a radiance field using the supervision from a pretrained text-to-image diffusion model and produces impressive 3D objects of diverse genres. Nonetheless, pretrained 2D generative networks only offer limited 3D knowledge and inevitably lead to blurry 3D results. A high-quality generation framework in 3D space is still highly desired.

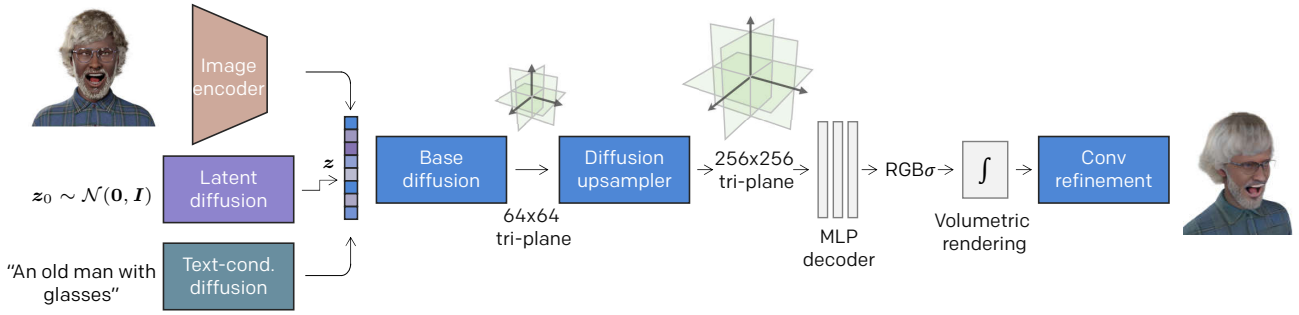

Figure 2. An overview of our RODIN model. We derive the latent $\boldsymbol{z}$ via the mapping from image, text, or random noise, which is used to control the base diffusion model to generate 64×64 tri-planes. We train another diffusion model to upsample this coarse result to 256×256 tri-planes that are used to render final multi-view images with volumetric rendering and convolutional refinement. The operators used in diffusion models are designed to be 3D-aware.

3. Approach

Unlike prior methods that learn 3D-aware generation from a 2D image collection, we aim to learn the 3D avatar generation using the multi-view renderings from the Blender synthetic pipeline [69]. Rather than treating the multi-view images of the same subject as individual training samples, we fit the volumetric neural representation for each avatar, which is used to explain all the observations from different viewpoints. Thereafter we use diffusion models to characterize the distribution of these 3D instances. Our diffusion-based 3D generation is a hierarchical process — we first utilize a diffusion model to generate the coarse geometry, followed by a diffusion upsampler for detail synthesis. As illustrated in Figure 2, the whole 3D portrait generation comprises multiple training stages, which we detail in the following subsections.

3.1. Robust 3D Representation Fitting

To train a generative network with explicit 3D supervision, we need an expressive 3D representation that accounts for multi-view images, which should meet the following requirements. First, we need an explicit representation that is amenable to generative network processing. Second, we require a compact representation that is memory efficient; otherwise, it would be too costly to store a myriad of such 3D instances for training. Furthermore, we expect fast representation fitting since hours of optimization as vanilla NeRF [38] would make it unaffordable to generate abundant 3D training data as required for generative modeling.

Taking these into consideration, we adopt *tri-plane representation* proposed by [9] to model the neural radiance field of 3D avatars. Specifically, the 3D volume is factorized into three axis-aligned orthogonal feature planes, denoted by $\boldsymbol{y}_{uv}, \boldsymbol{y}_{wu}, \boldsymbol{y}_{vw} \in \mathbb{R}^{H \times W \times C}$, each of which has spatial resolution of $H \times W$ and number of channel as C. Compared to voxel grids, the tri-plane representation offers a considerably smaller memory footprint without sacrificing the expressivity. Hence, rich 3D information is explicitly memorized in the tri-plane features, and one can query the feature of the 3D point $\boldsymbol{p} \in \mathbb{R}^3$ by projecting it onto each plane and aggregating the retrieved features, *i.e.*, $\boldsymbol{y}_{\boldsymbol{p}} = \boldsymbol{y}_{uv}(\boldsymbol{p}_{uv}) + \boldsymbol{y}_{wu}(\boldsymbol{p}_{wu}) + \boldsymbol{y}_{vw}(\boldsymbol{p}_{vw})$. With such positional feature, one can derive the density $\sigma \in \mathbb{R}^+$ and view-dependent color $\boldsymbol{c} \in \mathbb{R}^3$ of each 3D location given the viewing direction $\boldsymbol{d} \in \mathbb{S}^2$ with a lightweight MLP decoder $\mathcal{G}_\theta^{\text{MLP}}$, which can be formulated as

$$\boldsymbol{c}(\boldsymbol{p}, \boldsymbol{d}), \sigma(\boldsymbol{p}) = \mathcal{G}_\theta^{\text{MLP}}\big(\boldsymbol{y}_{\boldsymbol{p}}, \xi(\boldsymbol{y}_{\boldsymbol{p}}), \boldsymbol{d}\big). \tag{1}$$

Here, we apply the Fourier embedding operator $\xi(\cdot)$ [64] on the queried feature rather than the spatial coordinate. The tri-plane features and the MLP decoder are optimized such that the rendering of the neural radiance field matches the multi-view images $\{\boldsymbol{x}\}_{N_v}$ for the given subject, where $\boldsymbol{x} \in \mathbb{R}^{H_0 \times W_0 \times 3}$. We enforce the rendered image given by volumetric rendering [37], *i.e.*, $\hat{\boldsymbol{x}} = \mathcal{R}(\boldsymbol{c}, \sigma)$, to match the corresponding ground truth with mean squared error loss. Besides, we introduce sparse, smooth, and compact regularizers to reduce the "floating" artifacts [3] in free space. For more tri-plane fitting details, please refer to the Appendix.

While prior per-scene reconstruction mainly concerns the fitting quality, our 3D fitting procedure should also con-

(a) 256×256 tri-plane (b) 64×64 tri-plane without random scaling (c) 64×64 tri-plane with random scaling

Figure 3. While 256×256 tri-planes give good renderings (a), the 64×64 variant gives much worse result (b). Hence, we introduce random scaling during fitting so as to obtain a robust representation that can be effectively rendered in continuous scales (c).

sider several key aspects for generation purposes. First, the tri-plane features of different subjects should rigorously reside in the same domain. To achieve this, we adopt a shared MLP decoder when fitting distinct portraits, thus implicitly pushing the tri-plane features to the shared latent space recognizable by the decoder. Second, the MLP decoder has to possess some level of *robustness*. That is, the decoder should be tolerant to slight perturbation of tri-plane features, and thus one can still obtain plausible results even if the tri-plane features are imperfectly generated. More importantly, the decoder should be robust to varied tri-plane sizes because hierarchical 3D generation is trained on multi-resolution tri-plane features. As shown in Figure 3, when solely fitting 256×256 tri-planes, its 64×64 resolution variant cannot be effectively rendered. To address this, we randomly scale the tri-plane during fitting, which is instrumental in deriving multi-resolution tri-plane features simultaneously with a shared decoder.

3.2. Latent Conditioned 3D Diffusion Model

Now the 3D avatar generation is reduced to learning the distribution of tri-plane features, *i.e.*, $p(\boldsymbol{y})$, where $y = (\boldsymbol{y}_{uv}, \boldsymbol{y}_{wu}, \boldsymbol{y}_{vw})$. Such generative modeling is non-trivial since $\boldsymbol{y}$ is highly dimensional. We leverage diffusion models for the task, which have shown compelling quality in complex image modeling.

On a high level, the diffusion model generates $\boldsymbol{y}$ by gradually reversing a Markov forward process. Starting from $\boldsymbol{y}_0 \sim p(\boldsymbol{y})$, the forward process q yields a sequence of increasing noisy latent codes $\{\boldsymbol{y}_t \mid t \in [0, T]\}$ according to $\boldsymbol{y}_t := \alpha_t \boldsymbol{y}_0 + \sigma_t \boldsymbol{\epsilon}$, where $\boldsymbol{\epsilon} \in \mathcal{N}(\mathbf{0}, \boldsymbol{I})$ is the added Gaussian noise; α_t and σ_t define a noise schedule whose log signal-to-noise ratio $\lambda_t = \log[\alpha_t^2 / \sigma_t^2]$ linearly decreases with the timestep t. With sufficient noising steps, we reach a pure Gaussian noise, *i.e.*, $\boldsymbol{y}_T \sim \mathcal{N}(\mathbf{0}, \boldsymbol{I})$. The generative process corresponds to reversing the above noising process, where the diffusion model is trained to denoise $\boldsymbol{y}_t$ into $\boldsymbol{y}_0$ for all t using a mean squared error loss. Following [24], better generation quality can be achieved by parameterizing the diffusion model $\hat{\boldsymbol{\epsilon}}_\theta$ to predict the added noise:

$$\mathcal{L}_{\text{simple}} = \mathbb{E}_{t, \boldsymbol{x}_0, \boldsymbol{\epsilon}} \left[\left\| \hat{\boldsymbol{\epsilon}}_\theta(\alpha_t \boldsymbol{y}_0 + \sigma_t \boldsymbol{\epsilon}, t) - \boldsymbol{\epsilon} \right\|_2^2 \right]. \quad (2)$$

In practice, our diffusion model training also jointly optimizes the variational lower bound loss $\mathcal{L}_{\text{VLB}}$ as suggested in [40], which allows high-quality generation with fewer timesteps. During inference, stochastic ancestral sampler [24] is used to generate the final samples, which starts from the Gaussian noise $\boldsymbol{y}_T$ and sequentially produces less noisy samples $\{\boldsymbol{y}_T, \boldsymbol{y}_{T-1}, \ldots\}$ until reaching $\boldsymbol{y}_0$.

We first train a base diffusion model to generate the coarse-level tri-planes, *e.g.*, at 64×64 resolution. A straightforward approach is to adopt the 2D network structure used in the state-of-the-art image-based diffusion models for our tri-plane generation. Specifically, we can concatenate the tri-plane features in the channel dimension as in [9], which forms $\boldsymbol{y} = (\boldsymbol{y}_{uv} \oplus \boldsymbol{y}_{wu} \oplus \boldsymbol{y}_{vw}) \in \mathbb{R}^{H \times W \times 3C}$, and employ a well-designed 2D U-Net to model the data distribution through the denoising diffusion process. However, such a baseline model produces 3D avatars with severe artifacts. We conjecture the generation artifact comes from the *incompatibility* between the tri-plane representation and the 2D U-Net. As shown in Figure 4(a), intuitively, one can regard the tri-plane features as the projection of neural volume towards the frontal, bottom, and side views, respectively. Hence, the channel-wise concatenation of these orthogonal planes for CNN processing is problematic because these planes are not spatially aligned. To better handle the tri-plane representation, we make the following efforts.

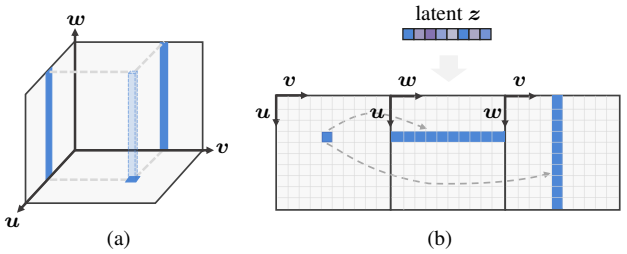

Figure 4. We propose two mechanisms to ensure coherent tri-plane generation. Our 3D-aware convolution considers the 3D relationship in (a) and correlates the associated elements from separate feature planes as shown in (b). In (b), we also visualize the usage of a shared latent code to orchestrate the feature generation.

3D-aware convolution. Using CNN to process channel-wise concatenated tri-planes will cause the mixing of theoretically uncorrected features in terms of 3D. One simple yet effective way to address this is to spatially *roll out* the tri-plane features. As shown in Figure 4(b), we concatenate the tri-plane features horizontally, yielding $\tilde{\boldsymbol{y}} = \texttt{hstack}(\boldsymbol{y}_{uv}, \boldsymbol{y}_{wu}, \boldsymbol{y}_{vw}) \in \mathbb{R}^{H \times 3W \times C}$. Such feature roll-out allows independent processing of feature planes. For simplicity, we subsequently use $\boldsymbol{y}$ to denote such input form by default. However, the tri-plane roll-out hampers cross-plane communication, while the 3D generation requires the synergy of the tri-plane generation.

To better process the tri-plane features, we need an efficient 3D operator that performs on the tri-plane rather than treating it as a plain 2D input. To achieve this, we propose *3D-aware convolution* to effectively process the tri-plane features while respecting their 3D relationship. A point on a certain feature plane actually corresponds to an axis-aligned 3D line in the volume, which also has two corresponding line projections in other planes, as shown in Figure 4(a). The features of these corresponding locations essentially describe the same 3D primitive and should be learned synchronously. However, such a 3D relationship is neglected when employing plain 2D convolution to tri-

plane processing. As such, our 3D-aware convolution explicitly introduces such 3D inductive bias by attending the features of each plane to the corresponding row/column of the rest planes. In this way, we enable 3D processing capability with 2D CNNs. This 3D-aware convolution applied on the tri-plane representation, in fact, is a generic way to simplify 3D convolutions previously too costly to compute when modeling high-resolution 3D volumes.

The 3D-aware convolution is depicted in Figure 4(b). Ideally, the compute for $\boldsymbol{y}_{uv}$ would attend to full elements from the corresponding row/column, *i.e.*, $\boldsymbol{y}_{wu}$ and $\boldsymbol{y}_{vw}$, from other planes. For parallel computing, we simplify this and aggregate the row/column elements. Specifically, we apply the axis-wise pooling for $\boldsymbol{y}_{wu}$ and $\boldsymbol{y}_{vw}$, yielding a row vector $\boldsymbol{y}_{wu\to u} \in \mathbb{R}^{1\times W\times C}$ and a column vector $\boldsymbol{y}_{vw\to v} \in \mathbb{R}^{H\times 1\times C}$ respectively. For each point of $\boldsymbol{y}_{uv}$, we can easily access the corresponding element in the aggregated vectors. We expand the aggregated vectors to the original 2D dimension (*i.e.*, replicating the column vectors along row dimension, and vice versa) and thus derive $\boldsymbol{y}_{(\cdot)u}, \boldsymbol{y}_{v(\cdot)} \in \mathbb{R}^{H\times W\times C}$. By far, we can perform 2D convolution on the channel-wise concatenation of the feature maps, *i.e.*, $\texttt{Conv2D}(\boldsymbol{y}_{uv} \oplus \boldsymbol{y}_{(\cdot)u} \oplus \boldsymbol{y}_{v(\cdot)})$. because $\boldsymbol{y}_{uv}$ is now spatially aligned with the aggregation of the corresponding elements from other planes. The compute for $\boldsymbol{y}_{vw}$ and $\boldsymbol{y}_{wu}$ is conducted likewise. The 3D-aware convolution greatly enhances the cross-plane communication, and we empirically observe reduced artifacts and improved generation of thin structures like hair strands.

Latent conditioning. We further propose to learn a latent vector to *orchestrate* the tri-plane generation. As shown in Figure 2, we additionally train an image encoder $\mathcal{E}$ to extract a semantic latent vector serving as the conditional input of the base diffusion model, so essentially the whole framework is an *autoencoder*. To be specific, we extract the latent vector from the frontal view of each training subject, *i.e.*, $\boldsymbol{z} = \mathcal{E}_\theta(\boldsymbol{x}_{\text{front}}) \in \mathbb{R}^{512}$, and the diffusion model conditioned on $\boldsymbol{z}$ is trained to reconstruct the tri-plane of the same subject. We use adaptive group normalization (AdaGN) to modulate the activations of the diffusion model, where $\boldsymbol{z}$ is injected into every residual block, and in this way, the features of the orthogonal planes are synchronously generated according to a shared latent.

The latent conditioning not only leads to higher generation quality but also permits a disentangled latent space, thus allowing semantic editing of generated results. To achieve better editability, we adopt a frozen CLIP image encoder [46] that has shared latent space with text prompts. We will show how the learned model produces controllable text-guided generation results.

Another notable benefit of latent conditioning is that it allows *classifier-free guidance* [25], a technique typically used to boost the sampling quality in the conditional generation. When training the diffusion model, we randomly zero the latent embedding with 20% probability, thus adapting the diffusion decoder to unconditional generation. During inference, we can steer the model toward better generation sampling according to

$$\hat{\boldsymbol{\epsilon}}_\theta(\boldsymbol{y}, \boldsymbol{z}) = \lambda \boldsymbol{\epsilon}_\theta(\boldsymbol{y}, \boldsymbol{z}) + (1-\lambda)\boldsymbol{\epsilon}_\theta(\boldsymbol{y}), \tag{3}$$

where $\boldsymbol{\epsilon}_\theta(\boldsymbol{y}, \boldsymbol{z})$ and $\boldsymbol{\epsilon}_\theta(\boldsymbol{y})$ are the conditional and unconditional $\boldsymbol{\epsilon}$-predictions respectively, and $\lambda > 0$ specifies the guidance strength.

Our latent conditioned base model thus supports both unconditional generation as well as the conditional generation that is used for portrait inversion. To account for full diversity during unconditional sampling, we additionally train a diffusion model to model the distribution of the latent $\boldsymbol{z}$, whereas the latent $\boldsymbol{y}_T$ describes the residual variation. We include this latent diffusion model in Figure 2.

3.3. Diffusion Tri-plane Upsampler

To generate high-fidelity 3D structures, we further train a diffusion super-resolution (SR) model to increase the tri-plane resolution from 64×64 to 256×256. At this stage, the diffusion upsampler is conditioned on the low-resolution (LR) tri-plane $\boldsymbol{y}^{\text{LR}}$. Different from the base model training we parameterize the diffusion upsampler $\boldsymbol{y}_\theta^{\text{HR}}(\boldsymbol{y}_t^{\text{HR}}, \boldsymbol{y}^{\text{LR}}, t)$ to predict the high-resolution (HR) ground truth $\boldsymbol{y}_0^{\text{HR}}$ instead of the added noise $\boldsymbol{\epsilon}$. The 3D-aware convolution is utilized in each residual block to enhance detail synthesis.

Following prior cascaded image generation works, we apply *condition augmentation* to reduce the domain gap between the output from the base model and the LR conditional input for SR training. We conduct careful tuning for the tri-plane augmentation with a combination of random downsampling, Gaussian blurring and Gaussian noises, making the rendered augmented LR tri-plane resemble the base rendering output as much as possible.

Nonetheless, we find that a tri-plane restoration with a lower ℓ_2 distance to the ground truth may not necessarily correspond to a satisfactory image rendering. Hence, we need to directly constrain the rendered image. Specifically, we obtain the rendered image $\hat{\boldsymbol{x}}^{\text{HR}} \in \mathbb{R}^{256\times256\times3}$ from the predicted tri-plane $\hat{\boldsymbol{y}}_0^{\text{HR}}$ with $\hat{\boldsymbol{x}} = \mathcal{R}(\mathcal{G}_\theta^{\text{MLP}}(\hat{\boldsymbol{y}}_0^{\text{HR}}))$, and we further penalize the perceptual loss [27] between this rendered result and the ground truth, according to

$$\mathcal{L}_{\text{perc}} = \mathbb{E}_{t,\hat{\boldsymbol{x}}} \sum_l \|\Psi^l(\hat{\boldsymbol{x}}) - \Psi^l(\boldsymbol{x})\|_2^2, \tag{4}$$

where Ψ^l denotes the multi-level feature extraction using a pretrained VGG. Usually, the volume rendering requires stratified sampling along each ray, which is computationally prohibitive for high-resolution rendering. Hence, we compute $\mathcal{L}_{\text{perc}}$ on random 112×112 image patches with high

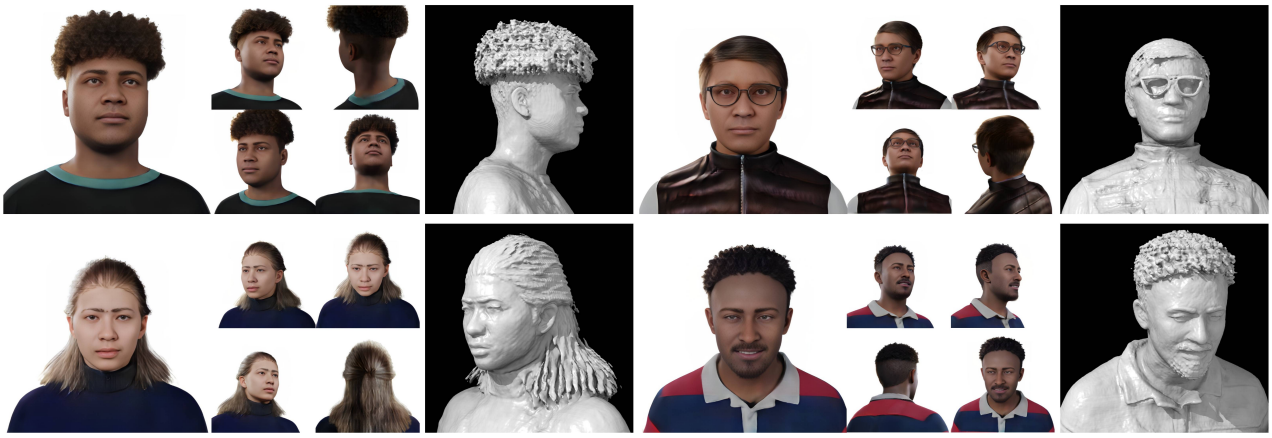

Figure 5. Unconditional generation samples by our RODIN model. We visualize the mesh extracted from the generated density field.

Figure 6. Latent interpolation results for generated avatars.

	Pi-GAN	GIRAFFE	EG3D	Autoencoder	Ours
FID ↓	78.3	64.6	40.5	67.4	**26.1**

Table 1. Quantitative comparison with baseline methods.

Model configuration	FID↓
A. Baseline	39.2
B. + Latent conditioning	37.4
C. + Tri-plane roll-out	28.4
D. + 3D-aware conv	**26.1**

Table 2. Ablation study of the proposed components.

sampling importance on face region. Compared with prior 3D-aware GANs that require rendering full images, our 3D-aware SR can be easily scalable to high resolutions due to the permit of patchwise training with direct supervision.

Modeling high-frequency detail and thin structures are particularly challenging in volumetric rendering. Thus, at this stage, we jointly train a convolution refiner [67] on our data which complements the missing details of the NeRF rendering, ultimately producing compelling 1024×1024 image outputs.

4. Experiments

4.1. Implementation Details

To train our 3D diffusion, we obtain 100K 3D avatars with a random combination of identities, expressions, hairstyles, and accessories using synthetic engine [69]. For each avatar, we render 300 multi-view images with known camera pose, which are sufficient for a high-quality radiance field reconstruction. The tri-planes for our generation have the dimension of $256 \times 256 \times 32$ in each feature plane. We optimize a shared MLP decoder when fitting the first 1,000 subjects. This decoder consists of 4 fully connected layers and is fixed when fitting the following subjects. Thus different subjects are fitted separately in distributed servers.

Both the base and upsampling diffusion networks adopt U-Net architecture to process the roll-out tri-plane features. We apply full-attention for 8^2, 16^2 and 32^2 scales within the network and adopt 3D-aware convolution at higher scales to enhance the details. While we generate 256^2 tri-planes with the diffusion upsampler, we also render image and compute image loss at 512^2 resolution, with a convolutional refinement further enhancing the details to 1024^2. For more details about the network architecture and training strategies, please refer to our Appendix.

4.2. Unconditional Generation Results

Figure 5 shows several samples generated by the RODIN model, showing the capability to synthesize high-quality 3D renderings with impressive details, *e.g.*, glasses and hairstyle. To reflect the geometry, we extract the mesh from the generated density field using marching cubes, which demonstrates high-fidelity geometry. More uncurated samples are shown in the Appendix. We also explore the interpolation of the latent condition $\boldsymbol{z}$ between two generated avatars, as shown in Figure 6, where we observe consistent high-quality interpolation results with smooth appearance transition.

Pi-GAN [10] GIRAFFE [41] EG3D [9] Our RODIN model

Figure 7. Qualitative comparison with state-of-the-art approaches.

4.3. Comparison

We compare our method with state-of-the-art 3D-aware GANs, *e.g.*, Pi-GAN [10] and GIRAFFE [41] and EG3D [9], which learn to produce neural radiance field from 2D image supervision. Moreover, we implement an auto-encoder baseline, which leverages the multi-view supervision and reconstructs the radiance field from the latent. We differ in this baseline by using the power diffusion-based decoder with 3D-aware designs. We adapt the official implementation of prior works to 360-degree generation and retrain them using the same dataset.

We use FID score [22] to measure the quality of image renderings. As per [30], we use the features extracted from the CLIP model to compute FID, which we find better correlates the perceptual quality. Specifically, we compute the FID score using 5K generated samples. The quantitative comparison is shown in Table 1, where we see that the RODIN model induces significantly lower FID than others.

The visual comparison in Figure 7 shows a clear quality superiority of our RODIN model over prior arts. Our method gives visually pleasing multi-view renderings with high-quality geometry, *e.g.*, for glasses and hair, whereas 3D-aware GANs produce more artifacts due to the geometry ambiguity caused by the simple use of image supervision.

4.4. Analysis of the RODIN model

Both 3D-aware convolution and latent conditioning are crucial for 3D synthesis. To prove this, we conduct the ablation study as shown in Table 2. We start from a baseline that uses a plain 2D CNN to process channel-wise concatenated tri-plane features following [9]. With latent conditioning, we achieve a lower FID. Feeding the network with roll-out tri-plane features significantly reduces the FID score because tri-planes are no longer improperly mingled. The proposed 3D-aware convolution further improves the synthesis quality, especially for thin structures like hair and cloth texture. More visual results regarding these ablations can be found in the Appendix.

Base diffusion Diffusion upsampler Convolutional refiner

Figure 8. Hierarchical generation progressively improves results.

Hierarchical generation is critical for high-fidelity results. One significant benefit of this approach is that we can train different diffusion models dedicated to different scales in a supervised manner, as opposed to end-to-end synthesis with image loss. This also enables patch-wise training without the need to render full images. Thus hierarchical training allows high-resolution avatar generation without suffering the prohibitive memory issue. Figure 8 shows the progressive quality improvement after the base diffusion, diffusion upsampler, and convolution refinement, respectively. It can be seen that the diffusion upsampler is critical, largely enhancing the synthesis quality, while convolution refinement further adds delicate details.

Diffusion upsampling training strategies. When training the tri-plane upsampler, we parameterize the model to predict the clean tri-plane ground truth at each diffusion re-

(a) (b)

Figure 9. Results of (a) portrait inversion and (b) text-to-avatar generation.

Tri-plane level loss	Image-level loss	Cond. augment	FID ↓
✓			48.5
✓	✓		38.6
✓	✓	✓	**26.1**

Table 3. Ablation study of the tri-plane upsampling strategy.

version step. Meanwhile, conditioning augmentation is of great significance to let the model generalize to the coarse-level tri-plane generated from the base model. Besides, we observe enforcing image-level loss is beneficial to final perceptual quality. The effectiveness of these strategies are quantitatively justified in Table 3.

4.5. Applications

3D portrait from a single image. We can hallucinate a 3D avatar from a single portrait by conditioning the base generator with the CLIP image embedding for that input image. Note that our goal is different from face/head reconstruction [13, 49], but to conveniently produce a personalized digital avatar for users. As shown in Figure 9(a), the generated avatars keep the main characteristics of the portrait, *e.g.*, expression, hairstyle, glass wearing, etc., while being 360-degree renderable.

Text-to-avatar generation. Another natural way to customize avatars is to use language guidance. To do this, we train a text-conditioned diffusion model to generate the CLIP image embedding used to semantically control the avatar generation. We use a subset of the LAION-400M dataset [53] containing portrait-text pairs to train this model. As shown in Figure 9(b), one can finely customize the avatars using detailed text descriptions.

Text-based avatar customization. We can also semantically edit generated avatars using text prompts. For a generated avatar with the CLIP image embedding $\boldsymbol{z}_i$, we can obtain a direction $\boldsymbol{\delta}$ in the CLIP's text embedding based on prompt engineering [44]. We assume colinearity between the CLIP's image and text embedding, thus we obtain the manipulated embedding as $\boldsymbol{z}_i + \boldsymbol{\delta}$, which is used to condition the generative process. As shown in Figure 10, we can achieve a wide variety of disentangled and meaningful control faithful to the text prompt.

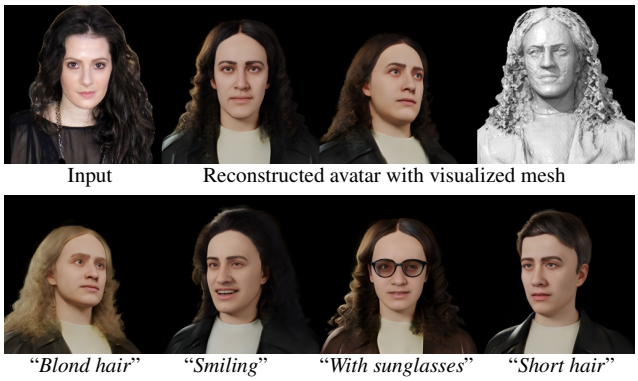

Figure 10. Results of text-guided avatar manipulation.

5. Discussion and Conclusion

We have presented the RODIN model, a powerful generative model for 3D avatars. Like all generative models, the RODIN model can exhibit biases that are inherited from the data it has been trained on. Some of these biases will be harmful and lead to an unfair representation for the target application. We need to pay attention to the data that are fed into RODIN and gain a better understanding of the resulting biases.

This model also allows users to customize avatars from a portrait or text, thus significantly lowering the barrier of personalized avatar creation. While this paper only focuses on avatars, the main ideas behind the RODIN model are applicable to the diffusion model for general 3D scenes. For future work, it would be fruitful to improve the sampling speed of the 3D diffusion model and study jointly leveraging the ample 2D data to mitigate the 3D data bottleneck.

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