ABSTRACT

This paper presents a new approach for 3D shape generation, enabling direct generative modeling on a continuous implicit representation in wavelet domain. Specifically, we propose a compact wavelet representation with a pair of coarse and detail coefficient volumes to implicitly represent 3D shapes via truncated signed distance functions and multi-scale biorthogonal wavelets, and formulate a pair of neural networks: a generator based on the diffusion model to produce diverse shapes in the form of coarse coefficient volumes; and a detail predictor to further produce compatible detail coefficient volumes for enriching the generated shapes with fine structures and details. Both quantitative and qualitative experimental results manifest the superiority of our approach in generating diverse and high-quality shapes with complex topology and structures, clean surfaces, and fine details, exceeding the 3D generation capabilities of the state-of-the-art models.

CCS CONCEPTS

• Computing methodologies → Shape analysis: Neural networks: Mesh models.

KEYWORDS

3D shape generation, diffusion model, wavelet representation

1 INTRODUCTION

Generative modeling of 3D shapes enables rapid creation of 3D contents, enriching extensive applications across graphics, vision, and VR/AR. With the emerging large-scale 3D datasets [Chang et al. 2015], data-driven shape generation has gained increasing attention from the research community recently. In general, a good 3D generative model should be able to produce diverse, realistic, and novel shapes, not necessarily the same as the existing ones.

Existing shape generation models are developed mainly for voxels [Girdhar et al. 2016; Yang et al. 2018; Zhu et al. 2017], point clouds [Achlioptas et al. 2018; Fan et al. 2017; Jiang et al. 2018], and meshes [Groueix et al. 2018; Smith et al. 2019; Tang et al. 2019; Wang et al. 2018]. Typically, these representations cannot handle high resolutions or irregular topology, thus unlikely producing high-fidelity results. In contrast, implicit functions [Chen and Zhang 2019; Mescheder et al. 2019; Park et al. 2019] show improved performance in surface reconstructions. By representing a 3D shape as a level set of discrete volume or a continuous field, we can flexibly extract a mesh object of arbitrary topology at desired resolution.
Existing generative models such as GANs and normalizing flows have shown great success in generating point clouds and voxels. Yet, they cannot effectively generate implicit functions. To represent a surface in 3D, a large number of point samples are required, even though many nearby samples are redundant. Taking the occupancy field for instance, only regions near the surface have varying data values, yet we need huge efforts to encode samples in constant and smoothly-varying regions. Such representation non-compactness and redundancy demands a huge computational cost and hinders the efficiency of direct generative learning on implicit surfaces.

To address these challenges, some methods attempt to sample in a pre-trained latent space built on the reconstruction task [Chen and Zhang 2019; Mescheder et al. 2019] or convert the generated implicit functions to point clouds or voxels for adversarial learning [Kleineberg et al. 2020; Luo et al. 2021]. However, these regularizations can only be indirectly applied to the generated implicit functions, so they are not able to ensure the generation of realistic objects. Hence, the visual quality of the generated shapes often shows a significant gap, as compared with the 3D reconstruction results, and the diversity of their generated shapes is also quite limited.

This work introduces a new approach for 3D shape generation, enabling direct generative modeling on a continuous implicit representation in the wavelet frequency domain. Overall, we have three key contributions: (i) a compact wavelet representation (i.e., a pair of coarse and detail coefficient volumes) based on biorthogonal wavelets and truncated signed distance field to implicitly encode values, yet we need huge efforts to encode samples in constant and smoothly-varying regions. Such representation non-compactness and redundancy demands a huge computational cost and hinders the efficiency of direct generative learning on implicit surfaces.

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This work introduces a new approach for 3D shape generation, enabling direct generative modeling on a continuous implicit representation in the wavelet frequency domain. Overall, we have three key contributions: (i) a compact wavelet representation (i.e., a pair of coarse and detail coefficient volumes) based on biorthogonal wavelets and truncated signed distance field to implicitly encode 3D shapes, facilitating effective learning of 3D shape distribution for shape generation; (ii) a generator network formulated based on the diffusion probabilistic model [Sohl-Dickstein et al. 2015] to produce coarse coefficient volumes from random noise samples, promoting the generation of diverse and novel shapes; and (iii) a detail predictor network, formulated to produce compatible detail coefficients to enhance the fine details in the generated shapes.

With the two trained networks, we can start from random noise volumes and flexibly generate diverse and realistic shapes that are not necessarily the same as the training shapes. Both quantitative and qualitative experimental results manifest the 3D generation capabilities of our method, showing its superiority over the state-of-the-art approaches. As Figure 1 shows, our generated shapes exhibit diverse topology, clean surfaces, sharp boundaries, and fine details, without obvious artifacts. Fine details such as curved/thin beams, small pulley, and complex cabinets are very challenging for the existing 3D generation approaches to synthesize.

2 RELATED WORK

3D reconstruction via implicit function. Recently, many methods leverage the flexibility of implicit surface for 3D reconstructions from voxels [Chen and Zhang 2019; Mescheder et al. 2019], complete/partial point clouds [Liu et al. 2021; Park et al. 2019; Yan et al. 2022], and RGB images [Li and Zhang 2021; Tang et al. 2021; Xu et al. 2019, 2020]. On the other hand, besides ground-truth field values, various supervisions have been explored to train the generation of implicit surfaces, e.g., multi-view images [Liu et al. 2019; Niemeyer et al. 2020] and unoriented point clouds [Atzmon and Lipman 2020; Gropp et al. 2020; Zhao et al. 2021]. Yet, the task of 3D reconstruction focuses mainly on synthesizing a high-quality 3D shape that best matches the input. So, it is fundamentally very

3D shape generation via implicit function. Unlike 3D reconstruction, the 3D shape generation task has no fixed ground truth to supervise the generation of each shape sample. Exploring efficient guidance for implicit surface generation is still an open problem. Some works attempt to use the reconstruction task to first learn a latent embedding [Chen and Zhang 2019; Hao et al. 2020; Ibing et al. 2021; Mescheder et al. 2019] then generate new shapes by decoding codes sampled from the learned latent space. Recently, [Hertz et al. 2022] learn a latent space with a Gaussian-mixture-based autodecoder for shape generation and manipulation. Though these approaches ensure a simple training process, the generated shapes have limited diversity restricted by the pre-trained shape space. Some other works attempt to convert implicit surfaces to some other representations, e.g., voxels [Kleineberg et al. 2020; Zheng et al. 2020], point cloud [Kleineberg et al. 2020], and mesh [Luo et al. 2021], for applying adversarial training. Yet, the conversion inevitably leads to information loss in the generated implicit surfaces, thus reducing the training efficiency and generation quality.

In this work, we propose to adopt a compact wavelet representation for modeling the implicit surface and learn to synthesize it with a diffusion model. By this means, we can effectively learn to generate the implicit representation without a pre-trained latent space and a representation conversion. The results also show that our new approach is capable of producing diversified shapes of high visual quality, exceeding the state-of-the-art methods.

Other representations for 3D shape generation. [Smith and Meger 2017; Wu et al. 2016] explore voxels, a natural grid-based extension of 2D image. Yet, the methods learn mainly coarse structures and fail to produce fine details due to memory restriction. Some other methods explore point clouds via GAN [Gal et al. 2020; Hui et al. 2020; Li et al. 2021], flow-based models [Cai et al. 2020; Kim et al. 2020], and diffusion models [Zhou et al. 2021]. Due to the discrete nature of point clouds, 3D meshes reconstructed from them often contain artifacts. This work focuses on implicit surface generation, aiming at generating high-quality and diverse meshes with fine details and overcoming the limitations of the existing representations.

Multi-scale neural implicit representation. This work also relates to multi-scale representations, so we discuss some 3D deep learning works in this area. [Chen et al. 2021; Chibane et al. 2020; Liu et al. 2020; Martel et al. 2021; Takikawa et al. 2021] predict multi-scale latent codes in an adaptive octree to improve the reconstruction quality and inference efficiency. [Fathony et al. 2020] propose a band-limited network to obtain a multi-scale representation by restricting the frequency magnitude of the basis functions. Recently, [Saragadam et al. 2022] adopt the Laplacian pyramid to extract multi-scale coefficients for multiple neural networks. Unlike our work, this work overfits each input object with an individual representation for efficient storage and rendering. In contrast to our work on shape generation, the above methods focus on improving 3D reconstruction performance by separately handling features at different levels. In our work, we adopt a multi-scale implicit representation based on wavelets (motivated by [Velho et al. 1994]) to build a compact representation for high-quality shape generation.
Denoising diffusion models. These models [Ho et al. 2020; Nichol and Dhariwal 2021; Sohl-Dickstein et al. 2015; Song et al. 2020] recently show top performance in image generation, surpassing GAN-based models [Dhariwal and Nichol 2021]. Very recently, [Luo and Hu 2021; Zhou et al. 2021] adopt diffusion models for point cloud generation. Yet, they fail to generate smooth surfaces and complex structures, as point clouds contain only discrete samples. Distinctively, we adopt diffusion model with a compact wavelet representation to model a continuous signed distance field, promoting shape generation with diverse structures and fine details.

3 OVERVIEW

Our approach consists of the following three major procedures:

(i) Data preparation is a one-time process for preparing a compact wavelet representation from each input shape; see Figure 2(a). For each shape, we sample a signed distance field (SDF) and truncate its distance values to avoid redundant information. Then, we transform the truncated SDF to the wavelet domain to produce a series of multi-scale coefficient volumes. Importantly, we take a pair of coarse and detail coefficient volumes at the same scale as our compact wavelet representation for implicitly encoding the input shape.

(ii) Shape learning aims to train a pair of neural networks to learn the 3D shape distribution from the coarse and detail coefficient volumes; see Figure 2(b). First, we adopt the denoising diffusion probabilistic model [Sohl-Dickstein et al. 2015] to formulate and train the generator network to learn to iteratively refine a random noise sample for generating diverse 3D shapes in the form of the coarse coefficient volume. Second, we design and train the detail predictor network to learn to produce the detail coefficient volume from the coarse coefficient volume for introducing further details in our generated shapes. Using our compact wavelet representation, it becomes feasible to train both the generator and detail predictor to successfully produce coarse coefficient volumes with plausible 3D structures and detail coefficient volumes with fine details.

(iii) Shape generation employs the two trained networks to generate 3D shapes; see Figure 2(c). Starting from a random Gaussian noise sample, we first use the trained generator to produce the coarse coefficient volume and then the trained detail predictor to further predict a compatible detail coefficient volume. After that, we can perform an inverse wavelet transform, followed by the marching cube operator [Lorensen and Cline 1987], to generate the output 3D shape.

4 METHOD

4.1 Compact Wavelet Representation

Preparing a compact wavelet representation from an input shape (see Figure 2(a)) involves the following two steps: (i) implicitly represent the shape using a signed distance field (SDF); and (ii) decompose the implicit representation via wavelet transform into coefficient volumes, each encoding a specific scale of the shape.

In the first step, we scale each shape to fit $[-0.45, +0.45]^3$ and sample an SDF of resolution $256^3$ to implicitly represent the shape. Importantly, we truncate the distance values in the SDF to $[-0.1, +0.1]$, so regions not close to object surface are clipped to a constant. We denote the truncated signed distance field (TSDF) for the $i$-th shape in training set as $S_i$. By using $S_i$, we can significantly reduce the shape representation redundancy and enable the shape learning process to better focus on the shape’s structures and fine details.

The second step is a multi-scale wavelet decomposition [Daubechies 1990; Mallat 1989; Velho et al. 1994] on
We denote the coarse and detail coefficient volumes at the wavelet decomposition, we follow [Velho et al. 1994] to efficiently which is roughly a compressed version of volume has a higher resolution than the coarser one, but both have vanishing moments with six for the synthesis filter and eight for the analysis filter; see Figures 3 (b) vs. (c). Also, instead of storing the detail predictor network to learn to predict $D^j_i$ from $C^j_i$ to enhance the details in the generated shapes.

Network structure. To start, we formulate a simple but efficient neural network structure for both the generator and detail predictor networks. The two networks have the same structure, since they both take a 3D volume as input and then output a 3D volume of same resolution as the input. Specifically, we adopt a modified 3D version of the U-Net architecture [Nichol and Dhariwal 2021]. We first apply 3D convolution to progressively compose and downsample the input into a set of multi-scale features and a bottleneck feature volume. Then, we apply a single self-attention layer to aggregate features in the bottleneck volume, so that we can efficiently incorporate non-local information into the features. Further, we upsample and concatenate features in the same scale and progressively perform an inverse convolution to produce an output of same size as the input. Note also that for all convolution layers in the network structure, we use a filter size of three with a stride of one.

Modeling the generator network. We formulate the 3D shape generation process based on the denoising diffusion probabilistic model [Sohl-Dickstein et al. 2015]. For simplicity, we drop the subscript and superscript in $C^j_i$, and denote $\{C_0, ..., C_T\}$ as the shape generation sequence, where $C_0$ is the target, which is $C^j_i$; $C_T$ is a random noise volume from the Gaussian prior; and $T$ is the total number of time steps. As shown on top of Figure 2(b), we have (i) a forward process (denoted as $q(C_0 | T)$) that progressively adds noises based on a Gaussian distribution to corrupt $C_0$ into a random noise volume; and (ii) a backward process (denoted as $p_0(C_0 | T)$) that employs the generator network (with network parameter $\theta$) to iteratively remove noise from $C_T$ to generate the target. Note that all 3D shapes $\{C_0, ..., C_T\}$ are represented as 3D volumes and each voxel value is a wavelet coefficient at its spatial location.

Both the forward and backward processes are modeled as Markov processes. The generator network is optimized to maximize the generation probability of the target, i.e., $p_0(C_0)$. Also, as suggested in [Ho et al. 2020], this training procedure can be further simplified to use the generator network to predict noise volume $e_\theta$. Hence, we adopt a mean-squares loss to train our framework:

$$L_2 = E_{t,C_0,e}[(\epsilon - e_\theta(C_t,t))^2], \epsilon \sim \mathcal{N}(0, I),$$

(1)

where $t$ is a time step; $\epsilon$ is a noise volume; and $\mathcal{N}(0, I)$ denotes a unit Gaussian distribution. In particular, we first sample noise volume $\epsilon$ from a unit Gaussian distribution $\mathcal{N}(0, I)$ and a time step $t \in [1, ..., T]$ to corrupt $C_0$ into $C_t$. Then, our generator network
Figure 4: Gallery of our generated shapes: Table, Chair, Cabinet, and Airplane (top to bottom). Our shapes exhibit complex structures, fine details, and clean surfaces, without obvious artifacts, compared with those generated by others; see Figure 5.

learns to predict noise $\epsilon$ based on the corrupted coefficient volume $C_T$. Further, as the network takes time step $t$ as input, we convert value $t$ into an embedding via two MLP layers. Using this embedding, we can condition all the convolution modules in the prediction and enable the generator to be more aware of the amount of noise contaminated in $C_T$. For more details on the derivation of the training objectives, please refer to the supplementary material.

4.3 Shape Generation

Now, we are ready to generate 3D shapes. First, we can randomize a 3D noise volume as $C_T$ from the standard Gaussian distribution. Then, we can employ the trained generator for $T$ iterations to produce $C_0$ from $C_T$. This process is iterative and inter-dependent. We cannot parallelize the operations in different iterations, so leading to a very long computing time. To speed up the inference process, we adopt an approach in [Song et al. 2020] to sub-sample a set of time steps from $[1, ..., T]$ during the inference; in practice, we evenly sample 1/10 of the total time steps in all our experiments.

After we obtain the coarse coefficient volume $C_0$, we then use the detail predictor network to predict detail coefficient volume $D_0$ from $C_0$. After that, we perform a series of inverse wavelet transforms from $\{C_0, D_0\}$ at scale $J=3$ to reconstruct the original TSDF. Hence, we can further extract an explicit 3D mesh from the reconstructed TSDF using the marching cube algorithm [Lorensen and Cline 1987]. Figure 2(c) illustrates the shape generation procedure.

4.4 Implementation Details

We employed ShapeNet [Chang et al. 2015] to prepare the training dataset used in all our experiments. Following the data split in [Chen and Zhang 2019], we use only the training split to supervise our network training. Also, similar to [Hertz et al. 2022; Li et al. 2021; Luo and Hu 2021], we train a single model for generating shapes of each category in the ShapeNet dataset [Chang et al. 2015].

We implement our networks using PyTorch and run all experiments on a GPU cluster with four RTX3090 GPUs. We follow [Ho et al. 2020] to set $(\beta_t)$ to increase linearly from $10^{-4}$ to 0.02 for 1,000 time steps and set $\sigma_t = \frac{1 - \eta t}{1 - \eta T} \beta_t$. We train the generator for 800,000 iterations and the detail predictor for 60,000 iterations, both using the Adam optimizer [Kingma and Ba 2014] with a learning rate of $10^{-4}$. Training the generator and detail predictor takes around three days and 12 hours, respectively. The inference takes around six seconds per shape on an RTX 3090 GPU. We adapt [Cotter 2020] to implement the 3D wavelet decomposition and will release our code and training data upon the publication of this work.
Table 1: Quantitative comparison between the generated shapes produced by our method and four state-of-the-art methods. We follow the same setting to conduct this experiment as in the state-of-the-art methods. From the table, we can see that our generated shapes have the best quality for almost all cases (lowest MMD, largest COV, and lowest 1-NNA) for both the Chair and Airplane categories. The units of CD and EMD are $10^{-3}$ and $10^{-2}$, respectively.

| Method            | Chair          |          | Airplane        |          |
|-------------------|----------------|----------|-----------------|----------|
|                   | COV CD EMD    | MMD CD EMD | 1-NNA CD EMD   | COV CD EMD | MMD CD EMD | 1-NNA CD EMD   |
| IM-GAN [Chen and Zhang 2019] | 56.49 54.50 11.79 14.52 61.98 63.45 | 61.55 62.79 3.320 8.371 76.21 76.08 |
| Voxel-GAN [Kleineberg et al. 2020] | 43.95 39.45 15.18 17.32 80.27 81.16 | 38.44 39.18 5.937 11.69 93.14 92.77 |
| Point-Diff [Luo and Hu 2021] | 51.47 55.97 12.79 16.12 61.76 63.72 | 60.19 62.30 3.543 9.519 74.60 72.31 |
| SPAGHETTI [Hertz et al. 2022] | 49.19 51.92 14.90 15.90 70.72 68.95 | 58.34 58.38 4.062 8.887 78.24 77.01 |
| Ours              | 58.19 55.46 11.70 14.31 61.47 61.62 | 64.78 64.40 3.230 7.756 71.69 66.74 |

Figure 5: Visual comparisons with state-of-the-art methods. Our generated shapes exhibit finer details and cleaner surfaces, without obvious artifacts.

5 RESULTS AND EXPERIMENTS

5.1 Galleries of our generated shapes

Besides Figure 1, we present Figure 4 to showcase the compelling capability of our method on generating shapes of various categories. Our generated shapes exhibit diverse topologies, fine details, and also clean surfaces without obvious artifacts, covering a rich variety of small, thin, and complex structures that are typically very challenging for the existing approaches to produce. More 3D shape generation results are provided in the supplementary material.

5.2 Comparison with Other Methods

Next, we compare the shape generation capability of our method with four state-of-the-art methods: IM-GAN [Chen and Zhang 2019], Voxel-GAN [Kleineberg et al. 2020], Point-Diff [Luo and Hu 2021], and SPAGHETTI [Hertz et al. 2022]. To our best knowledge, ours is the first work that generates implicit shape representations in frequency domain and considers coarse and detail coefficients to enhance the generation of structures and fine details.

Our experiments follow the same setting as the above works. Specifically, we leverage our trained model on the Chair and Airplane categories in ShapeNet [Chang et al. 2015] to randomly generate 2,000 shapes for each category. Then, we uniformly sample 2,048 points on each generated shape and evaluate the shapes using the same set of metrics as in the previous methods (details to be presented later). As for the four state-of-the-art methods, we employ publicly-released trained network models to generate shapes.

Evaluation metrics. Following [Hertz et al. 2022; Luo and Hu 2021], we evaluate the generation quality using (i) minimum matching distance (MMD) measures the fidelity of the generated shapes; (ii) coverage (COV) indicates how well the generated shapes cover the shapes in the given 3D repository; and (iii) 1-NN classifier accuracy (1-NNA) measures how well a classifier differentiates the generated shapes from those in the repository. Overall, a low MMD, a high COV, and an 1-NNA close to 50% indicate good generation quality. More details are provided in the supplementary material.

Quantitative Evaluation. Table 1 reports the quantitative comparison results, showing that our method surpasses all others for almost all the evaluation cases over the three metrics for both the Chair and Airplane categories. We employ the Chair category, due to its large variations in structure and topology, and the Airplane category, due to the fine details in its shapes. As discussed in [Luo and Hu 2021; Yang et al. 2019], the COV and MMD metrics have limited capabilities to account for details, so they are not suitable for measuring the fine quality of the generation results, e.g., the generated shapes sometimes show a better performance even when compared with the ground-truth training shapes on these metrics. In contrast, 1-NNA is more robust and can better correlate with the generation quality. In this metric, our approach outperforms all others, while having a significant margin in the Airplane category, manifesting the diversity and fidelity of our generated results.

Qualitative Evaluation. Figure 5 show some visual comparisons. For each random shape generated by our method, we find a similar shape (with similar structures and topology) generated by each of the other methods to make the visual comparison easier. See supplementary material Sections B and D for more visual comparisons. Further, as different methods likely have different statistical modes in the shape generation distribution, we also take random shapes generated by IM-GAN and find similar shapes generated by our
Figure 6: Shape novelty analysis. Top: From our generated shape (in green), we retrieve top-four most similar shapes (in blue) in training set by CD and LFD. Bottom: We generate 500 chairs using our method; for each chair, we retrieve the most similar shape in the training set by LFD; then, we plot the distribution of LFDs for all retrievals, showing that our method is able to generate shapes that are more similar (low LFDs) or more novel (high LFDs) compared to the training set. Note that the generated shape at 50th percentile is already not that similar to the associated training-set shape.

5.3 Model Analysis
Shape novelty analysis. Next, we analyze whether our method can generate shapes that are not necessarily the same as the training-set shapes, meaning that it does not simply memorize the training data. To do so, we use our method to generate 500 random shapes and retrieve top-four most similar shapes in the training set by LFD; then, we plot the distribution of LFDs for all retrievals, showing that our method is able to generate shapes that are more similar (low LFDs) or more novel (high LFDs) compared to the training set. Note that the generated shape at 50th percentile is already not that similar to the associated training-set shape.

Ablation Study. To evaluate the major components in our method, we conducted an ablation study by successively changing our full pipeline. First, we evaluate the generation performance with/without the detail predictor. Next, we study the importance of the diffusion model and the wavelet representation in the generator network.

The results in Table 2 demonstrate the capability of the detail predictor, which introduces a substantial improvement on all metrics (first vs. second rows). Further, replacing our generator with the VAD model or directly predicting TSDF leads to a performance degrade (second & last two rows). Due to the page limit, please refer to the supplementary material for the details on how the ablation cases are implemented and the visual comparison results.

Limitations. Due to the page limit, please refer to Section K of the supplementary material for the discussion on limitations.

6 CONCLUSION
This paper presents a new generative approach for learning 3D shape distribution and generating diverse, high-quality, and possibly novel 3D shapes. Unlike prior works, we operate on the frequency domain. By decomposing the implicit function in the form of TSDF using biorthogonal wavelets, we build a compact wavelet representation with a pair of coarse and detail coefficient volumes,
as an encoding of 3D shape. Then, we formulate our generator upon a probabilistic diffusion model to learn to generate diverse shapes in the form of coarse coefficient volumes from noise samples, and a detail predictor to further learn to generate compatible detail coefficient volumes for reconstructing fine details. Both quantitative and qualitative experimental results demonstrate the superiority of our method in generating diverse and realistic shapes that exhibit fine details, complex and thin structures, and clean surfaces, beyond the generation capability of the state-of-the-art methods.

To our best knowledge, this is the first work that successfully adopts a compact wavelet representation for an unconditional generative modeling on 3D shape generation, enabling many directions for future research. At first glance, our benefits can be extended to other downstream tasks with extra conditions, e.g., shape reconstruction from images or point clouds, and shape editing with user inputs. Another promising future direction is to adopt wavelet-based 3D generation to animation production, e.g., generating sequences of character motion with spatio-temporal wavelet representations. Also, we would like to explore more challenging cases, e.g., objects with extremely fine details and generation of 3D scenes.

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