Learning to Generate Wire Sculpture Art from 3D Models

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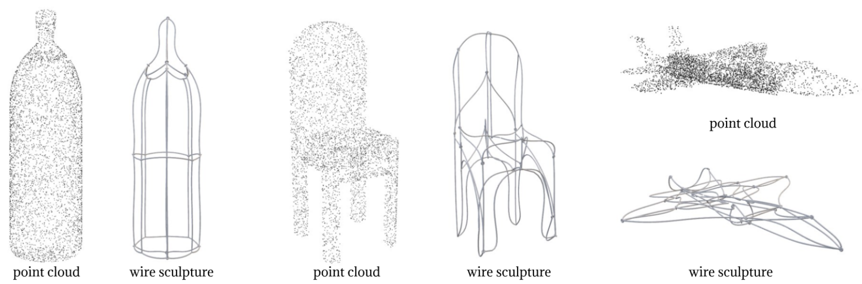

Figure 1: Our method transforms the input point clouds into wire sculptures that maximally preserve the original shape.

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1 INTRODUCTION

Creating line abstractions of 3D objects without being constrained by viewing angles is a non-trivial task. Previous methods [Yang et al. 2021; Yeh et al. 2022] usually do not consider viewing angles or focus on one single view. This means that the wire sculpture has to be viewed from a certain angle to deduce the original model. Compared with optimizing the wire configuration for a single view [Yang et al. 2021], our problem is more challenging since the multiple-view problem is essentially a larger problem optimizing across many individual views. Our approach to this problem is a template-based network. The goal is to create wire sculptures that preserve the volume of the original 3D shape given a user-specified template, e.g. an 8-vertex cube. The template provides a hard constraint on the topology. Besides, we also consider the smoothness of the wire to improve the aesthetics. The result of our method can correctly maintain the overall structure of the 3D model regardless of the view angle.

In our work, we propose a deep learning framework to generate 3D wire art based on 3D point clouds. Since this task is a large optimization problem, we adopt the deep learning technique because of its unique ability to optimize in a very large search space. Imagine how many ways we can position a curve on the surface of a complex 3D model. By training an end-to-end neural network, we enable the parameterized surface to fit the 3D shape's surface while preserving its topological structure. The trained model can directly predict a 3D curve representation that retains object features.

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2 METHOD

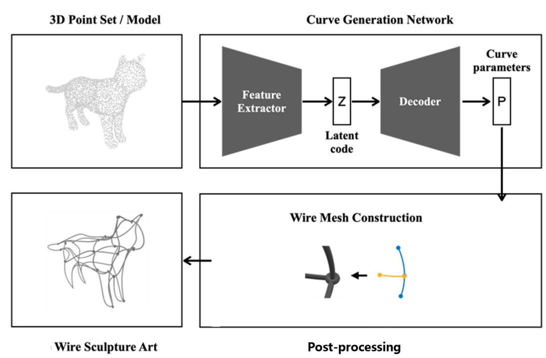

Figure 2: Method overview.

The overview of our proposed method is shown in Figure 2. Our objective is to take a point cloud as input and generate a wire model that effectively represents the object while preserving a sense of volume. If a 3D mesh is given, we can convert it into a point cloud simply by sampling.

Curve Generation Network. The output of the curve generation network is a set of cubic Bézier curves derived from a three-dimensional point cloud. The entire network is an encoder-decoder architecture, which consists of two main components: the *feature* *extractor* and the *curve decoder*. For the feature extractor network, we utilize a neural network based on EdgeConv [Wang et al. 2019] as our building block. EdgeConv performs a convolution operation on an input point and its neighbors to obtain aggregated edge features. The decoding network, on the other hand, consists of two fully connected layers (256, 128) followed by an output layer of dimension $3k$, where k represents the number of control points derived from the template. For example, a simple cube has 32 control points (four control points per cubic Bézier curve minus the shared vertices.)

Given a point cloud of n points: $\mathbf{X} = \{\mathbf{x_1}, \mathbf{x_2}, ..., \mathbf{x_n}\} \subseteq \mathbb{R}^3$, the entire generation network can produce a parameterized curve expressed as follows:

$$\mathbf{F}_\theta(\mathbf{X}) = \{\mathbf{c}_0, \mathbf{c}_1, ..., \mathbf{c}_{m-1}\},$$

where θ represents learnable network parameters and $\{\mathbf{c}_0, \mathbf{c}_1, ..., \mathbf{c}_{m-1}\}$ are m connected cubic Bézier curves segments.

Loss function. Our network is trained with the weight sum of three loss functions $L_{Chamfer}$, L_{kl}, and $L_{flatness}$. The chamfer loss ($L_{Chamfer}$) is to measure the distance between the fitted template and the input point cloud surface. We adopt the concept of Coons patches [Smirnov et al. 2021] to convert curve representation to surface. The other key loss function is the KL divergence for training the Variational Autoencoder. Additionally, we impose flatness loss to bias the network to generate smooth curves. The overall loss function is summarized as

$$L = L_{Chamfer} + L_{kl} + L_{flatness}$$

Post-processing. In this step, we convert the curves to a 3D mesh model as our final output. The curves are solidified by adding thickness to them. Toruses are used at the joint of two curves.

3 EXPERIMENTS

We use two datasets in our study: an animal point cloud dataset [Tulsiani et al. 2017] comprising 130 animal point clouds representing various species, and ShapeNet [Chang et al. 2015], a large-scale dataset with diverse 3D models.

We present the results generated by our method in Figure 1. Our proposed method demonstrates a good ability to retain point cloud contours from various viewpoints and effectively captures the sense of volume. Figure 3 depicts the wire art model generated from templates of different complexity. Because of our template-based approach, users can easily control the level of detail for their wire sculptures. Compared with the method that does not consider the viewing angles [Yeh et al. 2022], our result can better preserve the sense of volume. It is evident in Figure 4 that our result is more consistent across different views.

4 CONCLUSION

We propose a template-based approach for generating 3D wire art using neural networks, and it is self-supervised, requiring no labeled data. Our method takes a 3D model as input and produces artistic line models in three-dimensional space. However, we observe that the structure and connections of the lines are primarily constrained by templates, limiting the complexity of the generated line structures based on the given templates, especially for toroidal or more complex models. In the future, we aim to enhance our method to achieve better results on complex models with genus greater than zero, for example, a chair with a hole in it in Figure. 4(b).

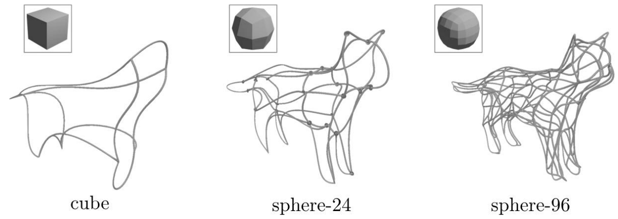

Figure 3: Wire sculptures generated given the same input point cloud but with different templates.

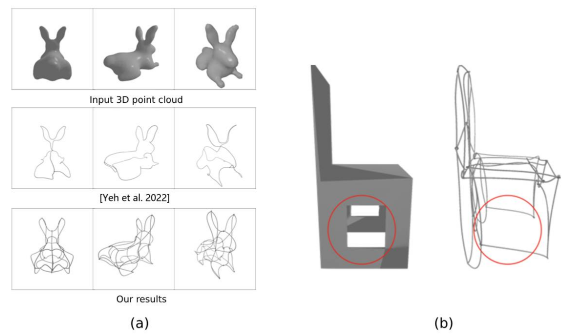

Figure 4: (a) Comparison of our method with Yeh et al.'s. (b) Our method fails at a chair with a hole in it.

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