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## Dynamic skeletonization via variational medial axis sampling

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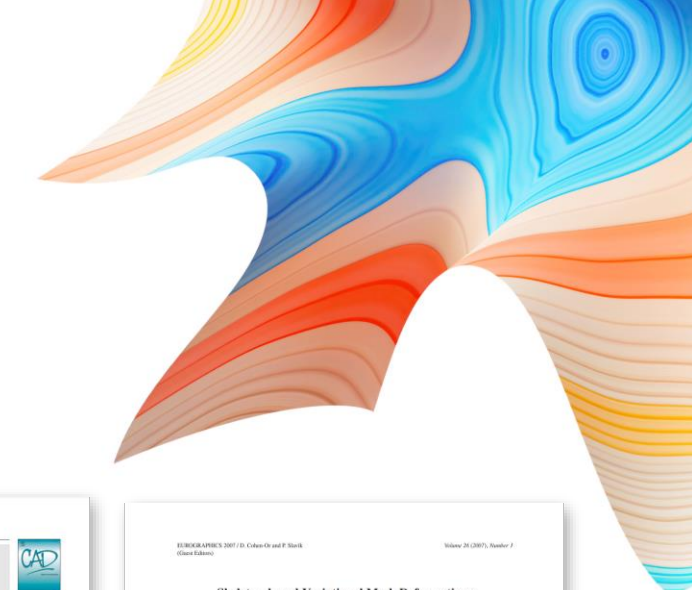
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# Skeleton: Valuable Tool



### Medial Elastics: Efficient and Collision-ready Deformation with Medial Axis Transform

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**Fig. 1.** Our framework optimizes medial reduction and collision detection via medial axis transform, a highly flexible and compact volumetric shape representation. The approximation follows the topological definition but does not simply serve as an expansion volume. In this sense, the right volume members fail to facilitate the collision detection and handling. In this figure, the background has 4000 vertices and 230k triangles. Following a semi-automated projection deformation, the result is reduced to a 2.2D-dimensional volume with 4000 vertices and 230k triangles. The restoration cost is  $\sim 10^5$  voxels with all the collisions and self-collisions resolved and with local detail preserved.

We propose a framework for the interactive animation of nonlinear deformable objects. The primary focus of our system is the seamless integration of deformable simulation and collision calling, which can often independently hinder in existing animation systems. To this end, we construct the medial axis transform or MAT, a highly flexible volumetric approximation of complex 3D shapes. From the precise simulation perspective, MAT is generally more useful than linear interpolated spheres for the so-called medial projection to approximate the boundary of the input model. The connection lies between two models: identified as a quadratically constrained quadratic program problem. We give an algorithm to solve this problem efficiently, which reduces the degree of freedom between a pair of intersecting medial primitives. When coupled with rapid building operations (including self-collisions) on the fly, we identify the OCF within few milliseconds over the massive simulation. We have built our system as a suite of generatively complex and high-resolution deformable objects, and our system produces convincing animation with all the collision-ready collision-ready handles at an interactive rate.

**CCS Concepts:** **Computing methodologies**  $\rightarrow$  **Stochastic analysis**; **Mesh models**.

**1. Introduction**

The progress of physical simulation in scientific research and industry has led to an increased demand for high-quality models as a simulation support. Hexahedral meshes, in fact, are often favored for their numerical properties and the potential for optimization during simulation [15, 16]. As a result, the number of research projects focused on the generation of hexahedral meshes has seen an exponential increase in recent years [18, 22]. However, the automatic generation of high-quality hexahedral meshes [18] is the boundary of the domain or the stability of the parameterized hexahedral meshes as a result. This can be an issue

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CCF 141932,30F

### Meso-Skeleton Guided Hexahedral Mesh Design

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**Fig. 1.** An overview of hexahedral meshes generated by our pipeline with the corresponding meso-skeletons used as support.

**Abstract**

We present a novel approach for the generation of hexahedral meshes for a volume domain given its meso-structure. This compact representation of the topology and geometry, composed of both curve and surface parts, is used to produce a set of decomposition of the domain into hexahedral blocks. Analysis of the different kinds of configurations of the domain leads to the construction of a set of convex surfaces that are used as a guide to form the hexahedral blocks. These local configurations of the domain completely determine the configuration of the final mesh. By following the skeleton, the geometry of the produced mesh naturally follows the geometry of the domain. Depending on the local user needs, the obtained mesh can be further adapted, refined or optimized. For example, we focus on the boundary of the domain. Our algorithm does not involve the generation of any global problem, most decisions are taken locally and it is thus highly suitable for parallel processing. This efficiency allows the user to iteratively refine the mesh for the correction or addition of the meso-structure for which a first sketch can be given by the existing meso-structure extraction algorithm.

**CCS Concepts:** **Computing methodologies**  $\rightarrow$  **Stochastic analysis**; **Mesh models**.

**1. Introduction**

General purpose meshing methods usually fall within one of a few categories based on the used approach. These categories usually comprise of grid and octree-based [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14], advancing front [17, 18, 19, 20, 21], and feature-based generation [12, 13, 14, 15, 16, 22, 23]. Many of these methods aim to provide high quality hex meshes in a wide variety of cases. However, some of the quality-related methods are the production of elements whose geometry is not always aligned to the geometry of the boundary of the domain or the stability of the parameterized hexahedral meshes as a result. This can be an issue

ACM Reference Format: Vedula, P., Krauss, F., and Bickmann, D. 2024. Meso-Skeleton Guided Hexahedral Mesh Design. In Proceedings of the ACM SIGGRAPH Conference on Computer Graphics, August 2024, 1–11. <https://doi.org/10.1145/3661188.3661192>

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### SEG-MAT: 3D Shape Segmentation Using Medial Axis Transformation

Cheng Lin, Lingjie Liu, Changjian Li, Leif Kobelt, Bin Wang, Shiqing Xin, Wengping Wang

**Abstract**—Segmenting arbitrary 3D objects into constituent parts that are structurally meaningful is a fundamental problem encountered in a wide range of computer graphics applications. Existing methods for 3D shape segmentation suffer from complex geometry processing and heavy computation caused by using level-set based and topological segmentation results due to the lack of global information. We present an efficient method, called SEG-MAT, based on the medial axis transform (MAT) of the input shape. Specifically, with the rich geometric and structural information revealed by the MAT, we are able to develop a simple and principled approach to effectively identify the various types of junctions between different parts of a 3D shape. Extensive evaluations and comparisons show that our method outperforms the state-of-the-art methods in terms of segmentation quality and is also one order of magnitude faster.

**Index Terms**—Shape Analysis, Shape Segmentation, Medial Axis Transform, Geometry

**1. INTRODUCTION**

Automatically segmenting 3D shapes into structurally meaningful parts is an important problem in many applications of computer graphics and computer vision. Most existing methods can be roughly categorized into two classes based on their goals and techniques. The first class of methods is based on supervised learning and relies on annotated semantic labels. Basically, the semantic meanings are pre-defined consistently within a shape category, and then the semantic labels are manually associated on datasets to train the neural networks. The second class of methods uses geometrical analysis and can be either rule-based or unsupervised learning-based. These methods decompose shape by finding part boundaries where certain geometrical properties are met. Semantics<sup>1</sup> and geometrical properties are used. Semantics<sup>2</sup> and geometrical properties methods have different criteria and goals. The semantic segmentation methods aim to find the correspondences between shapes and pre-defined labels, but do not focus on the part instances; the geometrical segmentation methods predominantly follow the minimum rule [1] that, for each part should be locally convex, which is shown in Fig. 1. These methods also have different technical merits and applications to solve different problem settings. The semantic methods are used to represent abstract semantic meanings for a group of similar shapes in the same category, while handling a single shape as an unknown category or individual. The geometrical methods are not limited to pre-defined labels of the parts.

In this paper, we return to the classic method based on 3D shape (see Fig. 2). 3D shape segmentation driven by geometrical analysis can be used to guide various tasks including modeling [3], [4], retrieval [5], [6], mesh multi-resolution and compression [7], feature mapping [8], reverse engineering [9], etc. Also, a robust geometry-based shape segmentation method can facilitate the data association process of various data-driven methods for 3D shape analysis.

Although shape segmentation by geometrical analysis is a well-researched problem, existing methods still have some notable issues. (1) A desirable part may have complex

ACM Reference Format: Lin, C., Liu, L., Li, C., Kobelt, L., Wang, B., Xin, S., and Wang, W. 2024. SEG-MAT: 3D Shape Segmentation Using Medial Axis Transformation. In Proceedings of the ACM SIGGRAPH Conference on Computer Graphics, August 2024, 1–11. <https://doi.org/10.1145/3661188.3661192>

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### IMMAT: Mesh Reconstruction from Single View Images by Medial Axis Transform Prediction

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**Abstract**

The reconstruction of a 3D object is a key problem for capturing the overall structure, as well as the local details. In this paper, we propose to predict a mesh representation of the Medial Axis Transform (MAT) of the input shape from a single view image. Because the MAT contains the skeleton topology and local thickness information, it not only enhances the ability to reconstruct topologically complex shapes but also better preserves the local details with its thickness control. The framework consists of three modules. The first module predicts the medial axes inside the shape surface and the energy function module predicts the topological relationships (relations) between the predicted axes. Then, the MAT (including visible surfaces) is predicted from the medial axes and the relations and the surface is reconstructed by inverting the predicted MAT on an implicit surface through CSG operation and then extracting the boundary surface through Marching Cubes. Experimental results show that our method outperforms the state-of-the-art methods both quantitatively and qualitatively on the reconstruction task.

**1. Introduction**

Inferring a 3D shape from a single view image has attracted much attention in recent years but is still a very challenging problem in various fields of computer vision and computer graphics. With the availability of large 3D shape datasets, such as ShapeNet [1], Deep learning based approaches can generate 3D shapes with representation of volume [2, 4], point clouds [2, 5], or triangular mesh [6] at the output of neural networks.

Geometry and topology are two important features of a 3D shape and shapes are often visually different from each other due to the difference in geometry and topology. Purely data-driven methods only express the geometry and have poor ability to learn the topology of 3D shapes.

Triangular mesh representation generally topology at the same time. However, it is difficult to learn topology from a single view image with explicit neural networks. The methods based on implicit mesh deformation [7] have shown that geometry affects the visual effect.

In this paper, we propose to predict the medial axes from a single view image. Different from skeleton points which are just clouds on the skeleton, MAT has more outstanding characteristics:

- (1) MAT uses medial spheres located on the skeleton with radii to represent the geometry. The value is the distance from the center of the sphere to the skeleton on the surface of the shape.

proving results, but they can only reconstruct shapes of very limited topologies that are often not complete models. Eliminating invalid triangular faces which cause the incorrect topology can be tedious through the topological operations of green topology, but it will destroy the closure of a mesh and cause boundary distortion. The skeleton-based method [1] has been proposed to capture the underlying topological structure of the target object. It is effective for reconstructing topologically complex shapes. However, the predicting skeleton points only provide an initial topology, which lacks geometry information to directly reconstruct the surface mesh. To learn better geometric structure, the skeleton points need to be transformed into visible and invisible. This step is able to absorb the disadvantage of mesh deformation, which may lead to self-intersection of the mesh or even deformation of the initial topology. The whole pipeline does not consider the thickness of the shape and leads to an incorrect result in the generated mesh that seriously affects the visual effect.

In this paper, we propose to predict the medial axes from a single view image. Different from skeleton points which are just clouds on the skeleton, MAT has more outstanding characteristics:

- (1) MAT uses medial spheres located on the skeleton with radii to represent the geometry. The value is the distance from the center of the sphere to the skeleton on the surface of the shape.

ACM Reference Format: Hu, J., Chen, G., Yang, B., Wang, N., Guo, X., and Wang, B. 2024. IMMAT: Mesh Reconstruction from Single View Images by Medial Axis Transform Prediction. In Proceedings of the ACM SIGGRAPH Conference on Computer Graphics, August 2024, 1–11. <https://doi.org/10.1145/3661188.3661192>

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### Skeleton-based Variational Mesh Deformations

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<sup>2</sup>MIT, USA

**Abstract**

In this paper, we propose a new free-form shape deformation approach. We combine a skeleton-based mesh deformation technique with discrete differential geometry in order to create natural-looking global shape deformations. Given a rough mesh, we first create an skeletal mesh, a non-aligned hexahedral approximation of the medial axis. Then the skeleton mesh is used for free-form deformations. Thus, a diverse global shape deformation is obtained by controlling the shape corresponding to the deformed skeletal mesh. The reconstruction is based on solving discrete differential equations. Our method preserves the geometric details and original shape thickness because of using discrete differential equations and skeleton-based deformations. We also develop a new mesh reduction technique which allows us to maintain possible global and local self-intersections of the deformed mesh while preserving fine geometric details. Finally, we present a mesh reduction version of our approach in order to simplify and accelerate the deformation process. In addition, increasing data between the proposed free-form shape deformations to unique and classical and modern methods in the differential geometry of sphere (compasses) are considered and discussed.

Categories and Index Descriptors according to ACM CCS: I.3.3 [Computer Graphics] Computational Geometry and Object Modeling

**1. Introduction**

Global free-form mesh deformations is an active research area which is greatly stimulated by advances in the digital manufacturing industry. Each year brings new approaches, such as combinations and reworking of old families [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100].

The idea of skeleton-based shape deformations was proposed by Blinn, the invention of the skeleton [100]. The Blinn skeleton is also known under the name of Medial Axis, but we prefer to call it "skeleton" since we generate 3D shapes as a set of surface meshes (global-together) in the current paper [101]. Blinn suggested that changes the skeleton of a plane figure while maintaining the object's width associated with the skeleton. In graphics and modeling, skeleton-based deformation techniques [102, 103, 104, 105] appeared as natural generalizations of methods [106] and convolution surfaces [107]. At

ACM Reference Format: Yuhzhen, S., Belyanov, A., and Seidel, H.-P. 2024. Skeleton-based Variational Mesh Deformations. In Proceedings of the ACM SIGGRAPH Conference on Computer Graphics, August 2024, 1–11. <https://doi.org/10.1145/3661188.3661192>

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**Simulation**  
 [Lan et al. 2020]

**Mesh Generation**  
 [Viville et al. 2023]

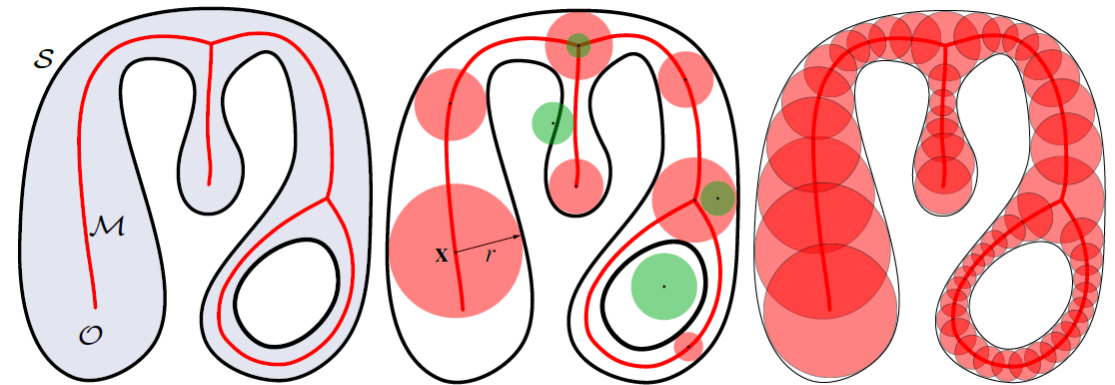
**Segmentation**  
 [Lin et al. 2020]

**Single Image Reconstruction**  
 [Hu et al. 2022]

**Deformation**  
 [Shin et al. 2007]

# Skeleton: Discretized Medial Axis

- **Medial Axis:** The set of centers of spheres that have at least two closest points on the boundary of the shape. Such a sphere is called a *medial sphere*



[Tagliasacchi et al. 2016]

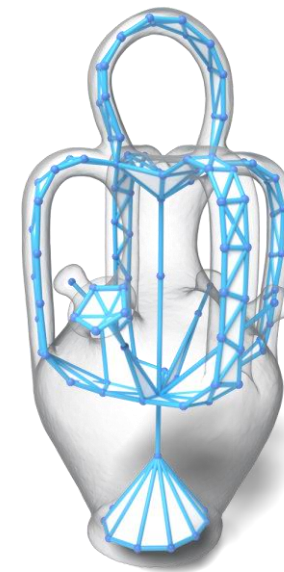
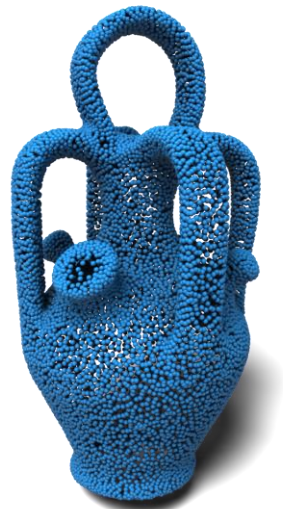


# Objective

Surface



Oriented Point cloud



Discretization of Medial Axis



# Medial Axis Approximation

Voronoi Diagram  
[Amenta et al. 1998]



Shrinking balls  
[Ma et al. 2013]



Random sampling  
[Dou et al. 2022][Wang et al. 2024]

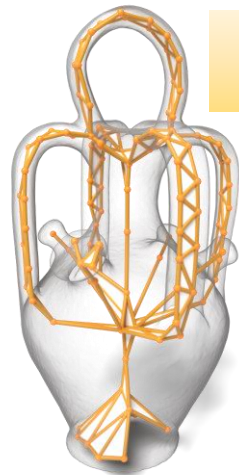


*Impractical for application*

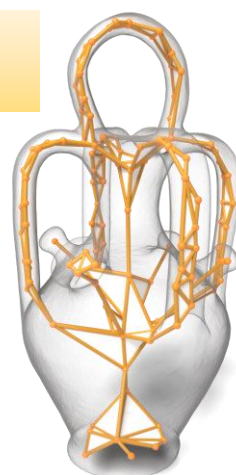
Simplification  
(Fine to Coarse)

Refinement ?

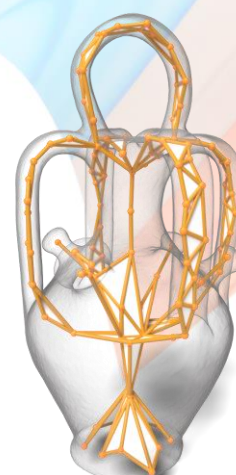
Q-MAT  
[Li et al. 2015]



Coverage Axis  
[Dou et al. 2022]



Coverage Axis++  
[Wang et al. 2024]



- Feature preservation
- Time consuming
- No control on the result
- Irregularity of the distribution of medial samples

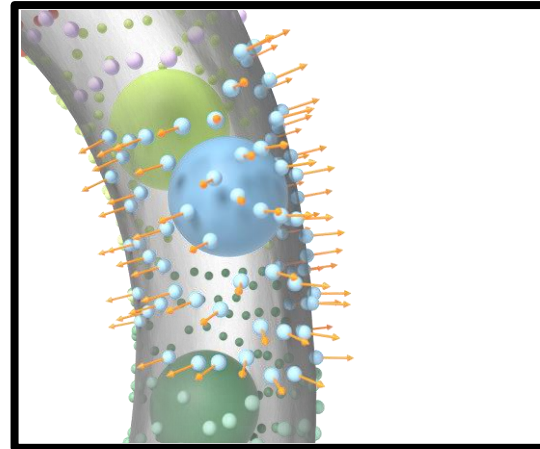
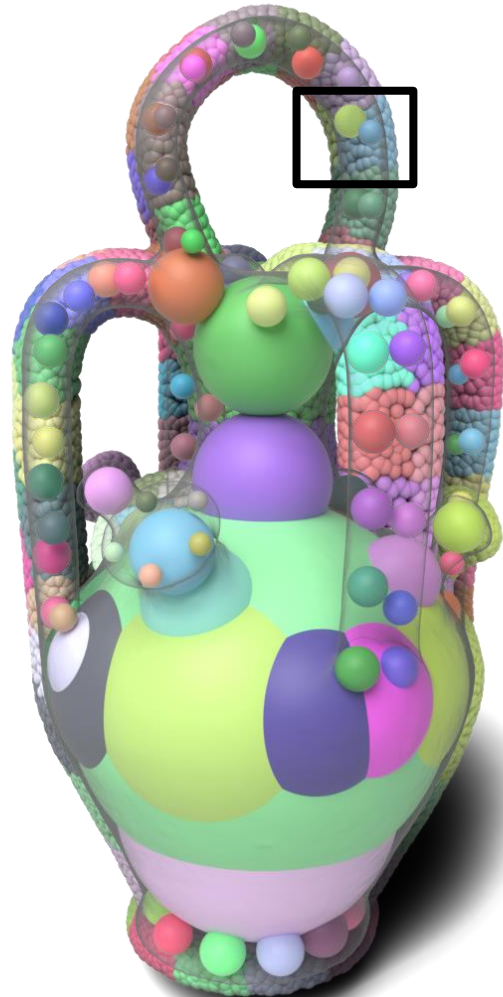


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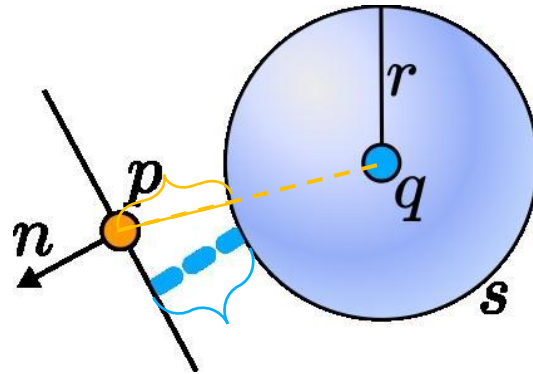
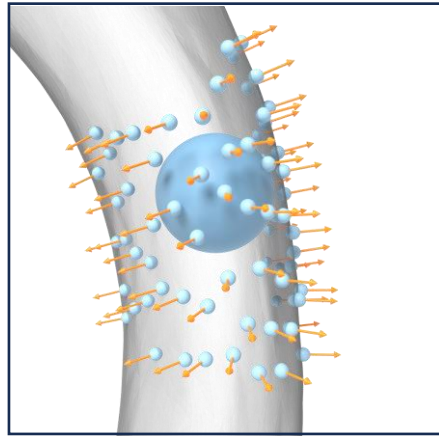
# Method



# Observation: Each medial sphere occupies a segment of surface



# Metric



- Sphere-plane distance:

$$d_{p,n}(s) = n^t \cdot (p - q) - r$$

- Spherical quadric error metric: [Thiery et al. 2013]

$$d_{p,n}(s)^2 = Q_{p,n}(s) = \frac{1}{2} s^t \cdot A \cdot s - b^t \cdot s + c$$

- Diffused quadric:

$$Q_{v_i}(s) = \sum_{t_j \in T(v_i)} \frac{\mathcal{A}(t_j)}{3} Q_{v_i, n_j}$$

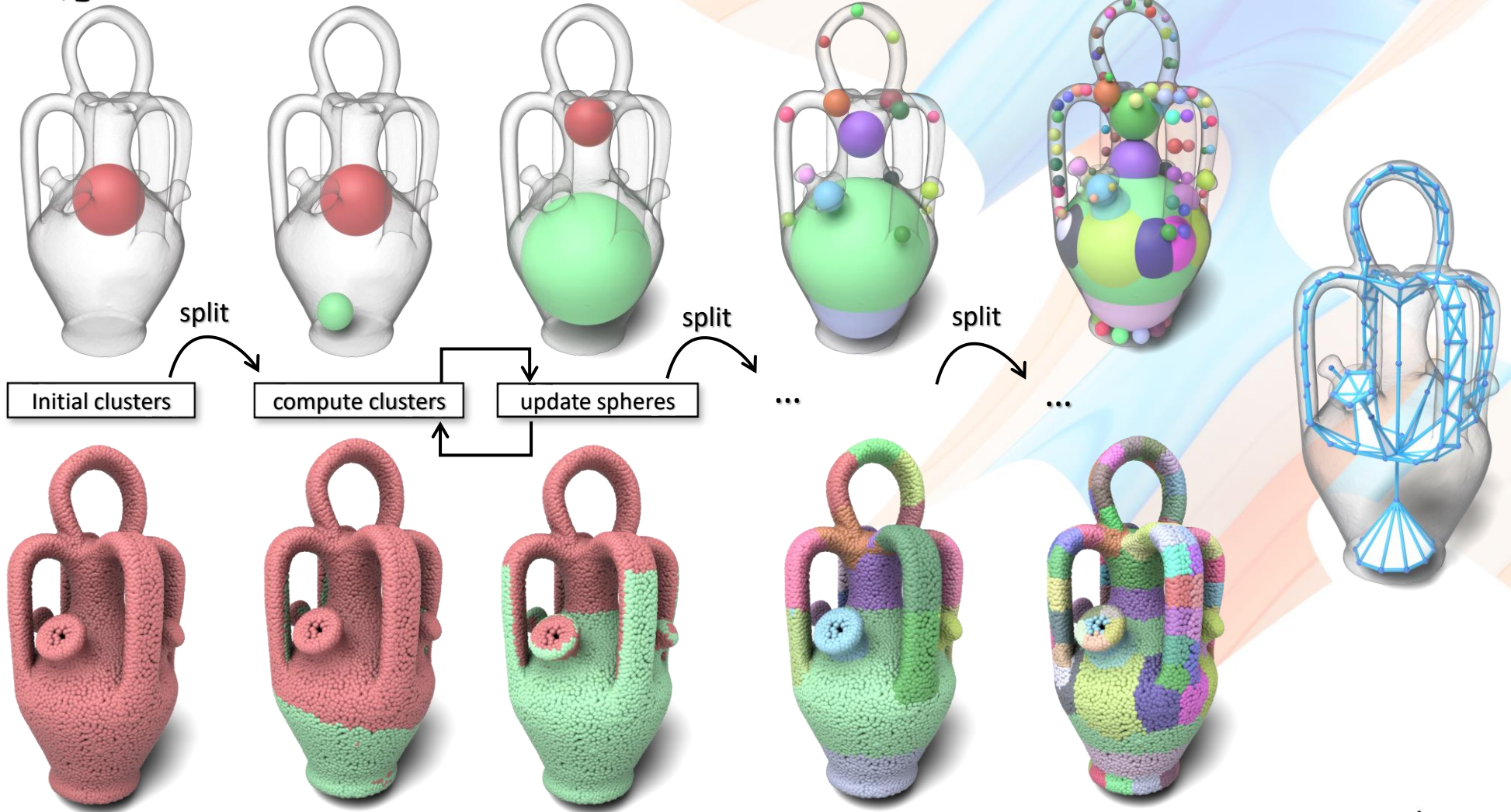
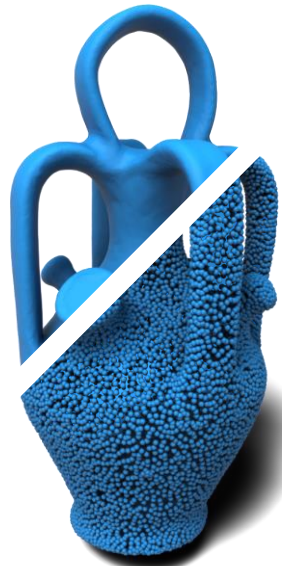
- Sphere-point distance:

$$D_{v_i}(s) = \left( \sum_{t_j \in T(v_i)} \frac{\mathcal{A}(t_j)}{3} \right) (|p - q| - r)^2$$

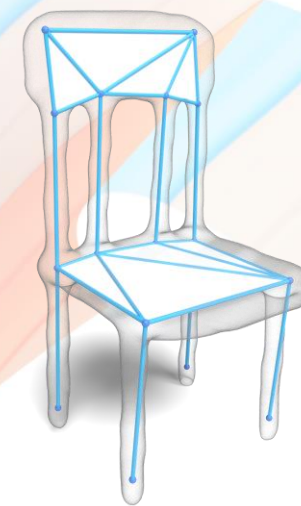
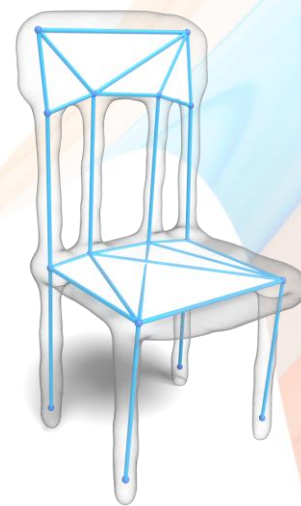
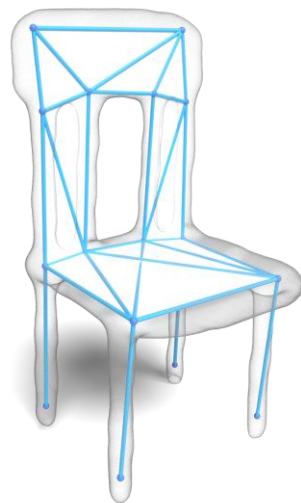
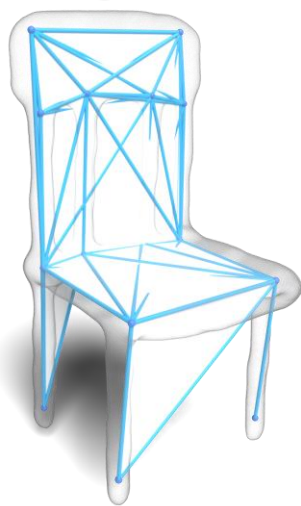
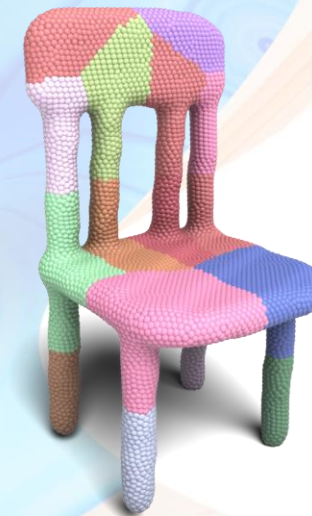
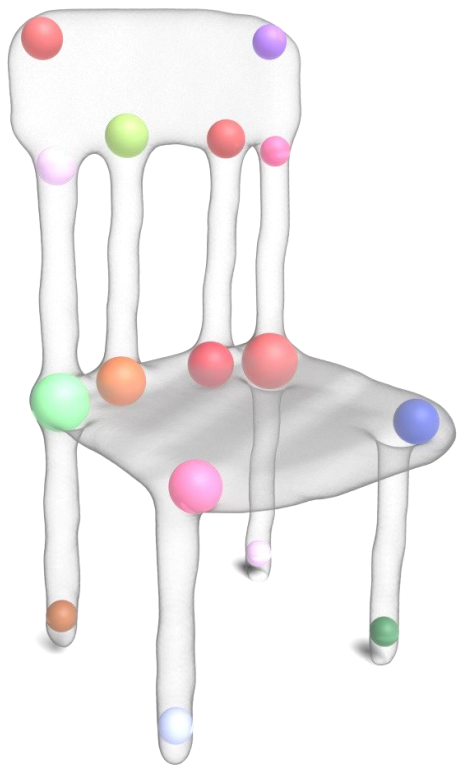
$\mathcal{A}(t_j)$ : area of triangle (KNN graph for point cloud)



# Pipeline



# Compute clusters



$$E_{v_i}(m_j) = Q_{v_i}(m_j) + \lambda D_{v_i}(m_j)$$

$\lambda = 0$

$\lambda = 0.02$

$\lambda = 0.2$

$\lambda = 1$



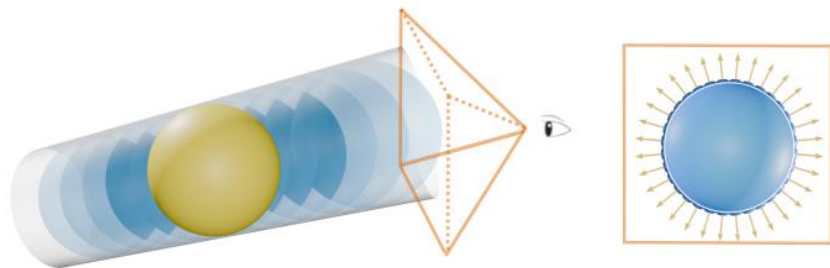
# Update spheres

- For each cluster vertices, fitting a sphere which minimizes the following metric:

$$(q_i^*, r_i^*) = \arg \min_{q_i, r_i} (E_{SQEM}(\mathcal{C}_i) + \lambda E_{euclidean}(\mathcal{C}_i))$$

$$E_{SQEM}(\mathcal{C}_i) = \sum_{v_j \in \mathcal{C}_i} Q_{v_j}(m_i)$$

$$E_{euclidean}(\mathcal{C}_i) = \sum_{v_j \in \mathcal{C}_i} D_{v_j}(m_i)$$



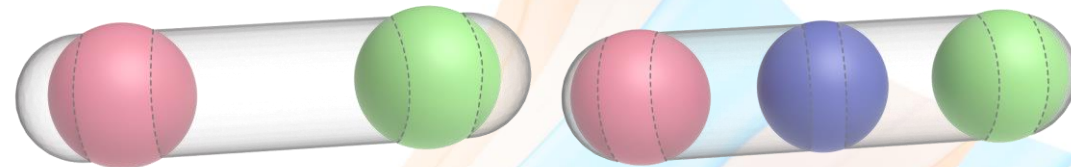
$\lambda = 0$



$\lambda = 0.2$



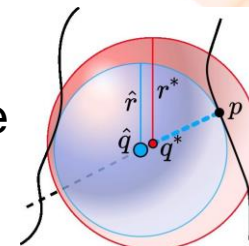
$\lambda = 1$



$|M| = 2$

$|M| = 3$

- No guarantee that the optimized sphere is medial sphere or within the shape
- Sphere Projection: Project the sphere center on the medial axis in the direction of the gradient of distance function.





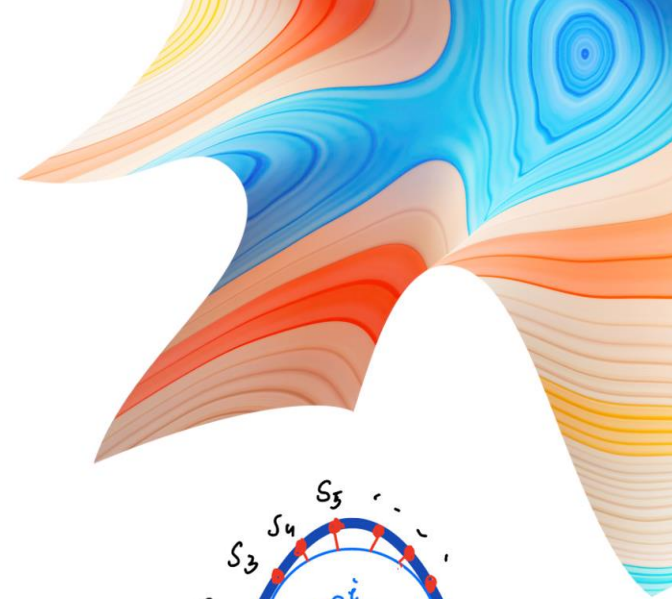
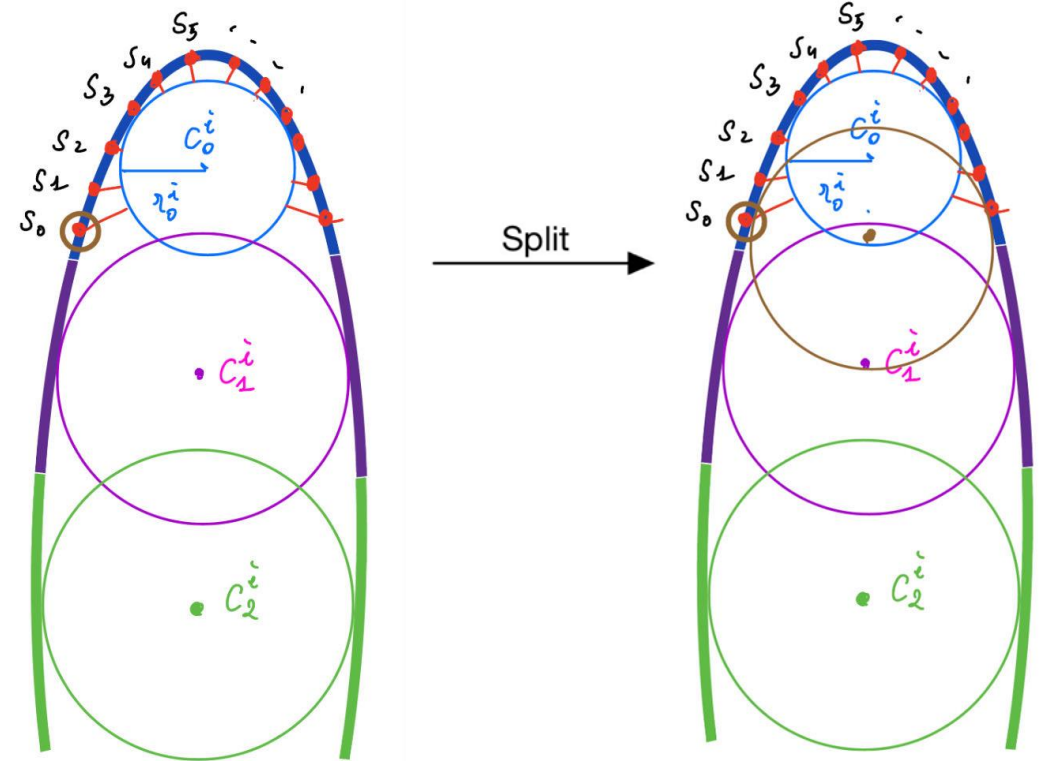
# Sphere splitting

- For each cluster  $C_i$  evaluate the error to determine whether it should be split.

$$E(C_i) = \frac{1}{\mathcal{A}(C_i)} \sum_{v_j \in C_i} E_{v_j}(m_i)$$

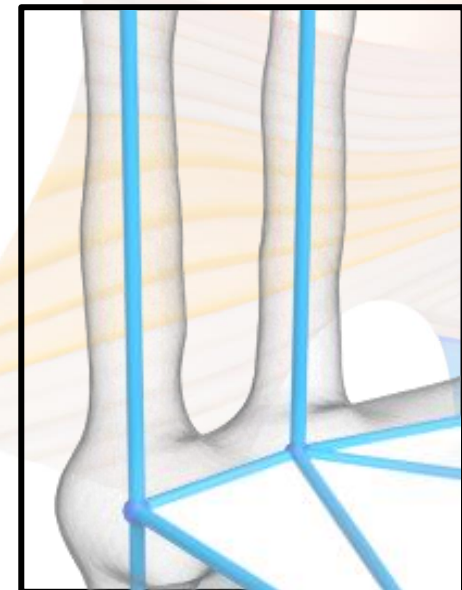
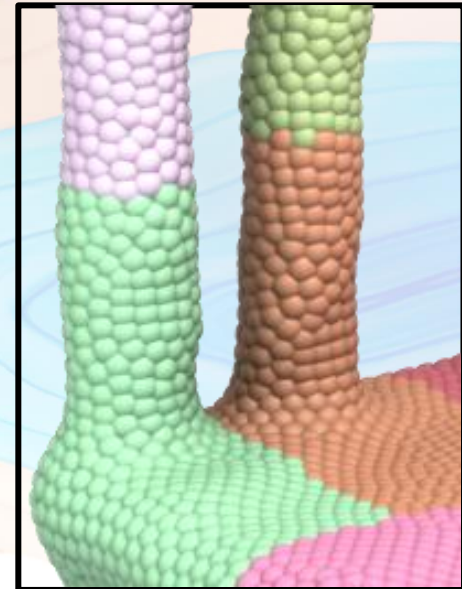
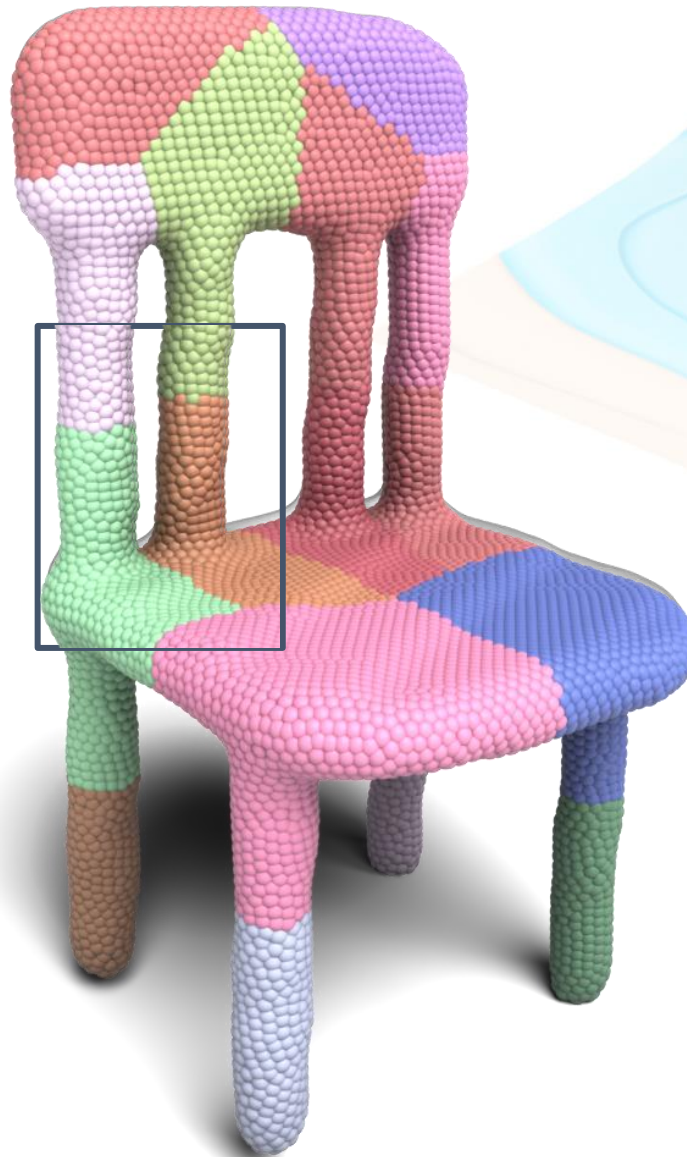
- Taking the vertex that has largest error as a seed to create a new sphere

$$v_{max} = \arg \max_{v_i \in C_i} E_{v_j}(m_i)$$



# Connectivity

- Build edge if two clusters are adjacent.
- Build face if three clusters share the same neighbours

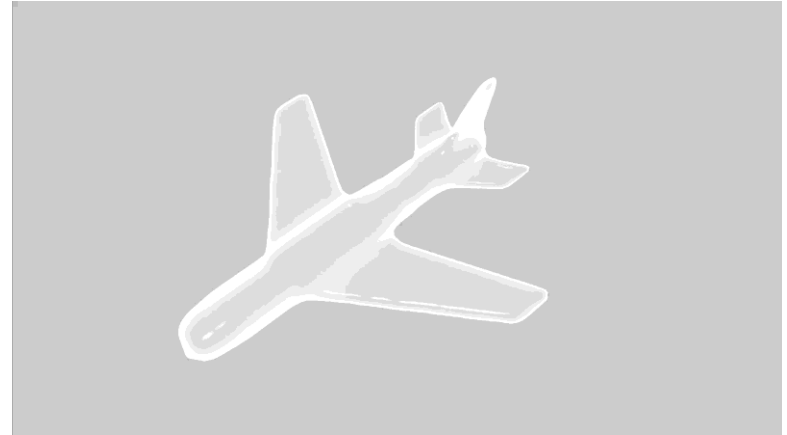
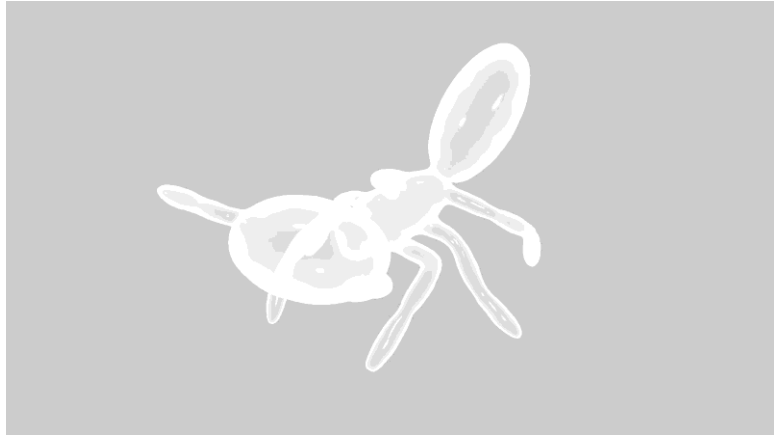
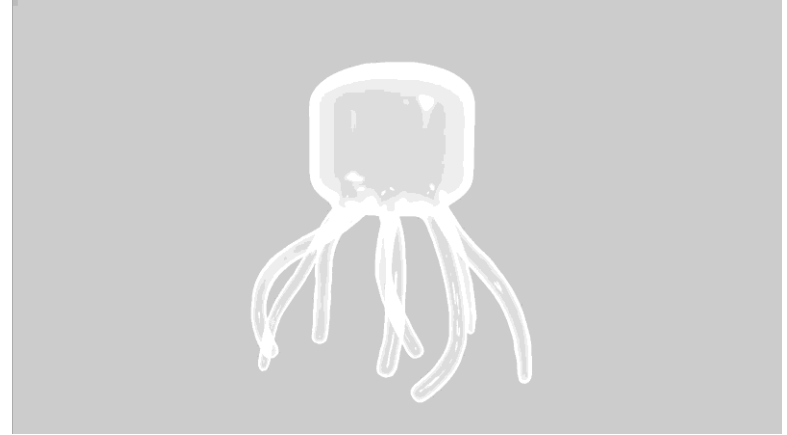




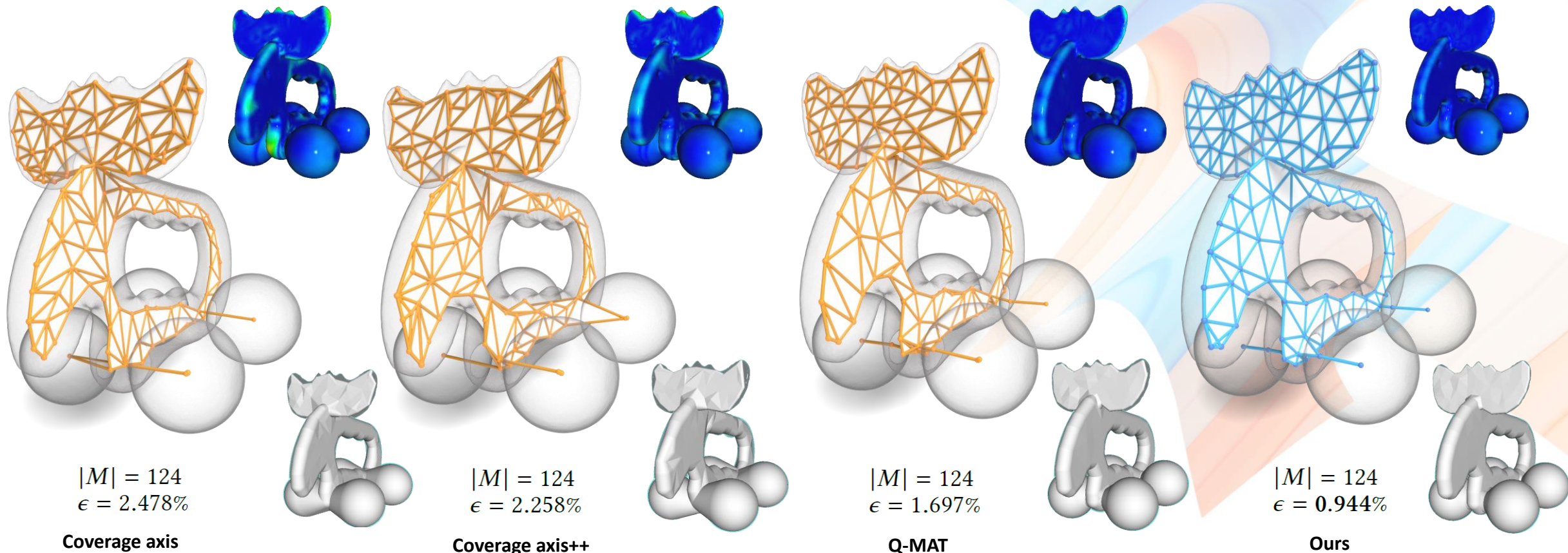
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**Result**





# Visual Comparison



$|M| = 124$   
 $\epsilon = 2.478\%$

Coverage axis

$|M| = 124$   
 $\epsilon = 2.258\%$

Coverage axis++

$|M| = 124$   
 $\epsilon = 1.697\%$

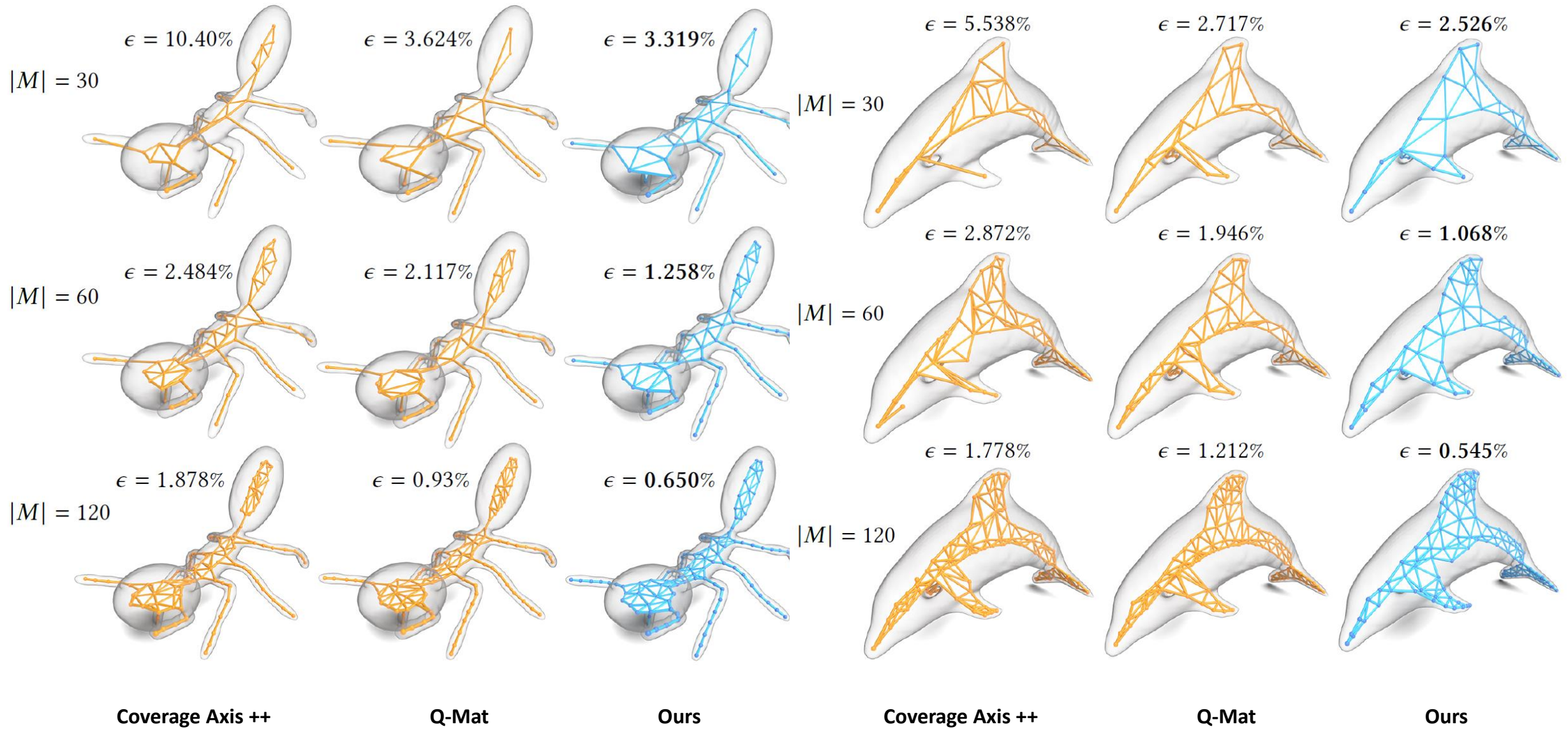
Q-MAT

$|M| = 124$   
 $\epsilon = 0.944\%$

Ours

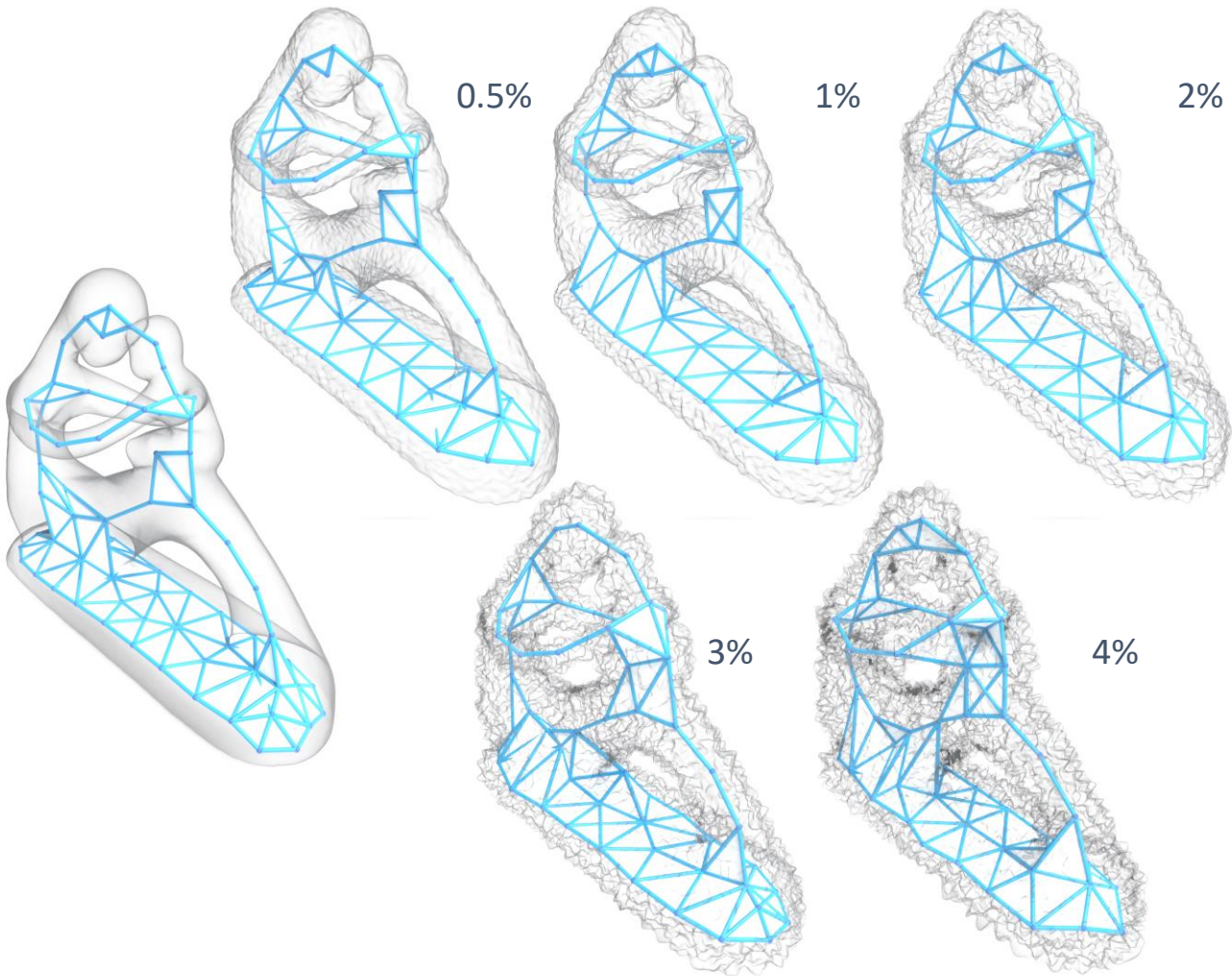


# Comparison: Different resolution

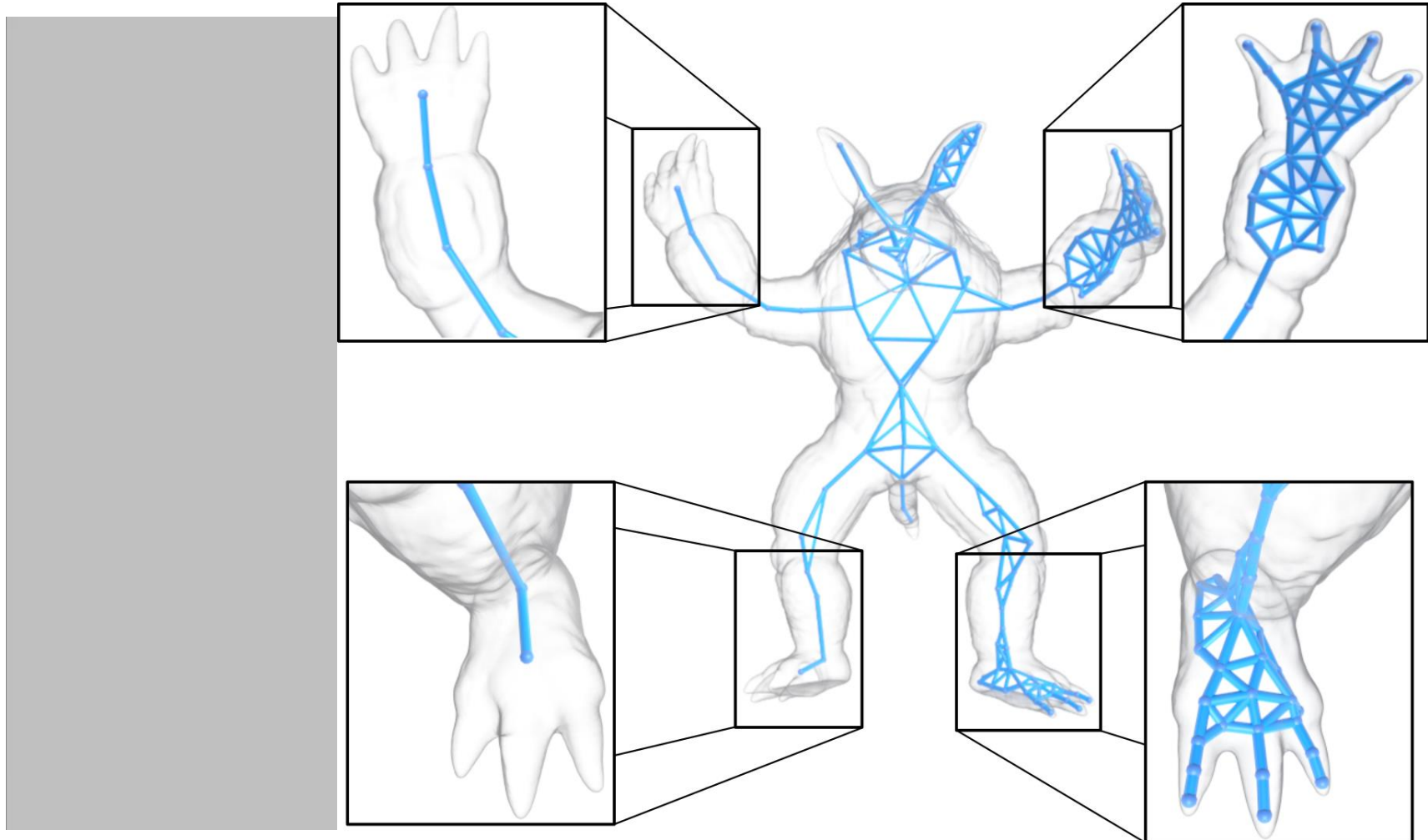




# Robustness to noise



# Interactive edition of skeleton



# Limitation and future work

## ● Limitation:

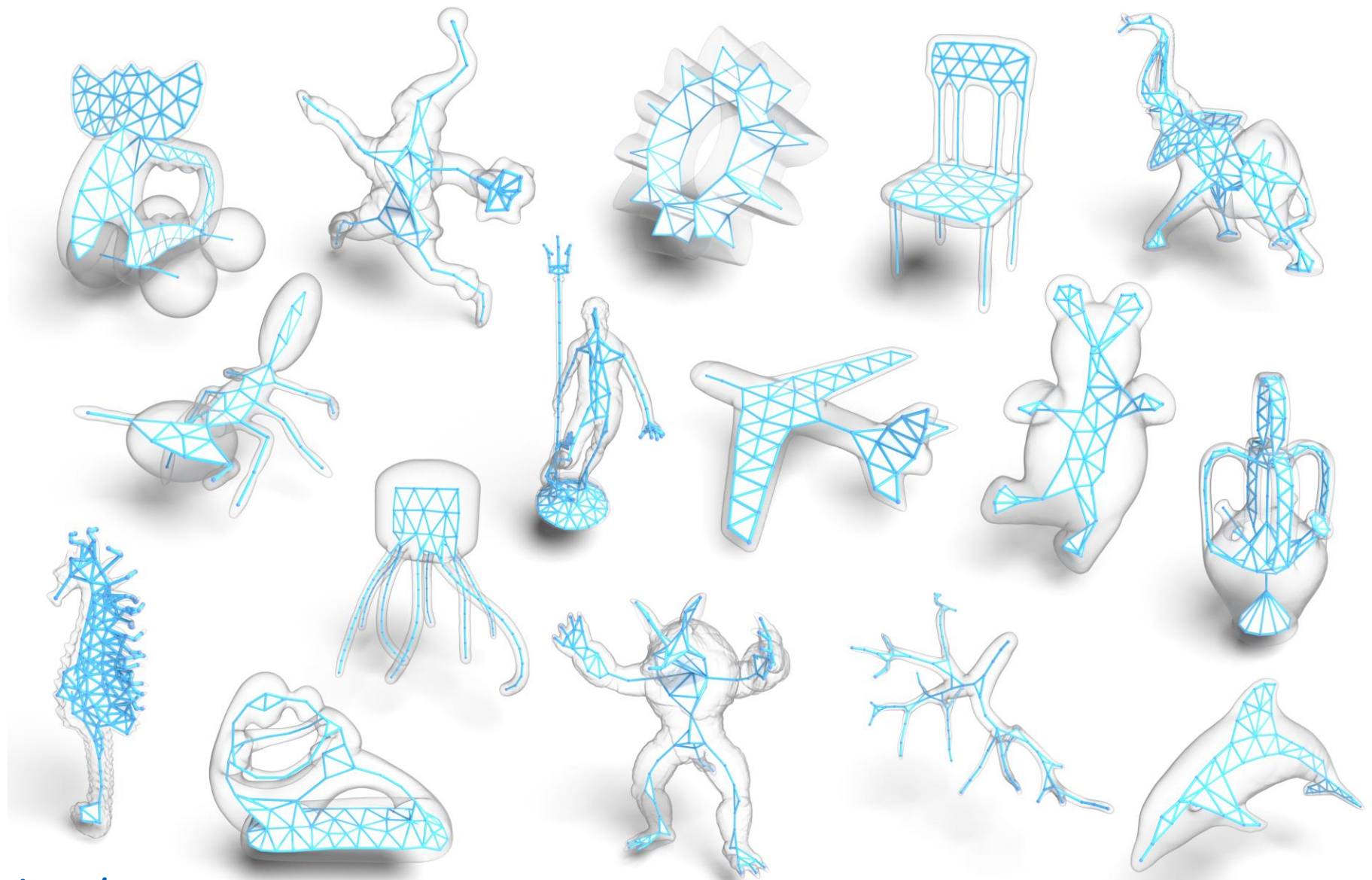
- **No Global Convergence:** There is potential for oscillations in the positions of medial spheres.
- **Topology Mismatch:** Coarse resolutions may result in a topology that differs from the input shape.
- **Suboptimal connectivity:** Intersecting triangles or closed surfaces may occur.

## ● Future work:

- **Medial Sample Freezing:** Lock samples in place to improve control.
- **Adaptive Density Function:** Enable region-specific refinement.
- **Support Diverse Inputs:** Extend to binary images or incomplete data.



# Gallery



Project page:  
<https://huang46u.github.io/VMAS>  
Code will release soon!

