Mixar Assignment: Adaptive Quantization and Seam Tokenization for 3D Mesh Reconstruction

Pranay Thakur - RA2211047010072
pt7109@srmist.edu.in

Overview

The task was to design and implement a 3D mesh quantization and analysis pipeline capable of:

1. Normalizing mesh coordinates.
2. Applying quantization to compress geometry.
3. Reconstructing the mesh and computing quantitative error metrics.
4. Optionally implementing a *bonus task* — seam detection and tokenization.

The goal was to demonstrate both algorithmic understanding and engineering precision. The project goes beyond the base requirements by introducing adaptive quantization, which dynamically adjusts bin resolution according to local vertex density, and by delivering a fully functional multi-cue seam tokenizer.

1. Adaptive Quantization Pipeline

1.1 Normalization

Each input mesh was first normalized under two schemes:

- **Min–Max Normalization:** rescales vertex coordinates along each axis independently to the [0,1] range.
- **Unit-Sphere Normalization:** centers the mesh at the origin and scales it so the maximum distance from the center is 1.

Both methods remove scale and translation dependencies, ensuring quantization results are comparable across meshes.

1.2 Density-Aware Region Binning

Uniform quantization divides the mesh space into fixed intervals regardless of geometric variation, which often leads to distortion in dense or complex regions.
Adaptive quantization corrects this by assigning bins proportional to local vertex density:

1. **Local Density Estimation**
   For each vertex, the average distance to its *k* nearest neighbors (k=16) is computed using a KD-tree.

2. **Clustering**
   The density values are grouped using *k-means* (k=4) to form spatial regions with similar geometric complexity.

3. **Bin Allocation**
   Each cluster receives a number of quantization bins proportional to its relative density:

$$b_{region} = \alpha \cdot b_{base} \cdot \frac{d_{region}}{\sum_i d_i}$$

   where α=1.0 is a scaling factor.

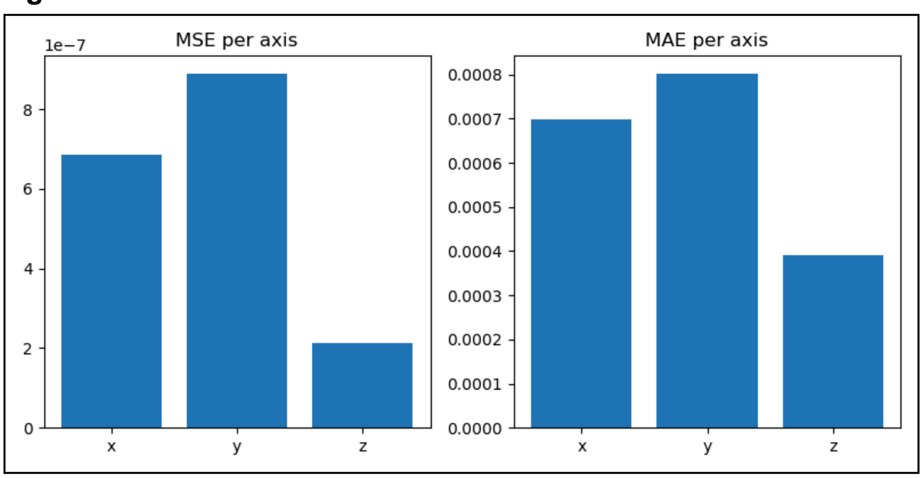
This ensures high-density areas (e.g., sharp corners, curved details) retain higher geometric fidelity, while smoother regions use coarser quantization.

1.3 Reconstruction and Metrics

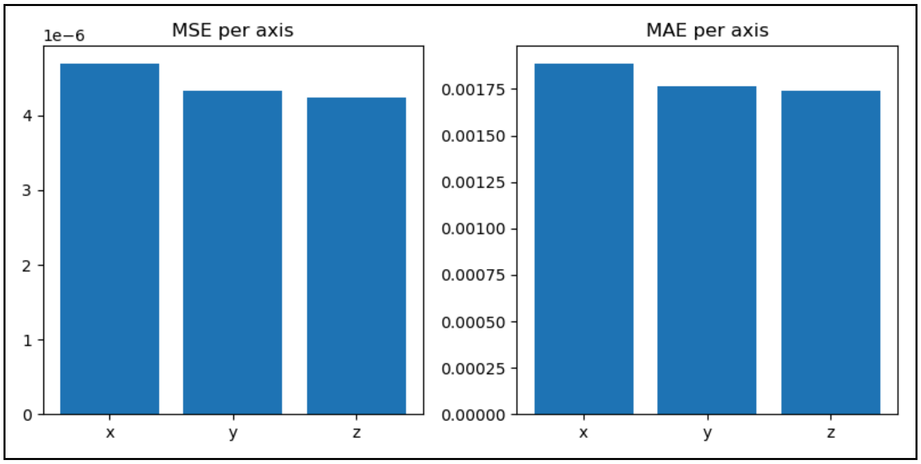
After quantization and dequantization, the mesh is denormalized back to its original coordinate range.
The reconstructed geometry is compared with the original using several complementary metrics:

Metric	Description	Insight
MSE/MAE per axis	Mean Squared and Absolute Error along X,Y,Z	Captures axis-wise numerical deviation
Chamfer Distance	Mean of nearest-neighbor distances (symmetric)	Measures global geometric similarity
Hausdorff Distance	Maximum deviation across point sets	Sensitive to outliers
Normal-Angle Error	Mean angular deviation between vertex normals	Indicates perceptual distortion

Figure 1: Error metrics for mesh Branch

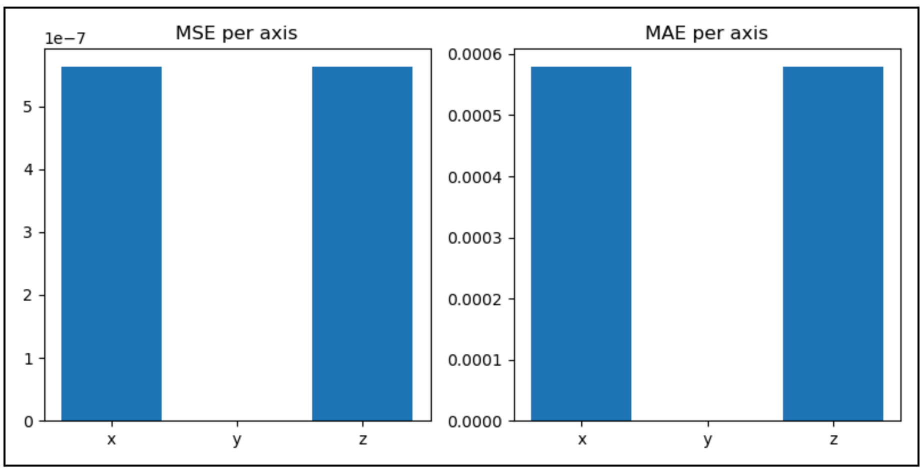


Minmax axis error

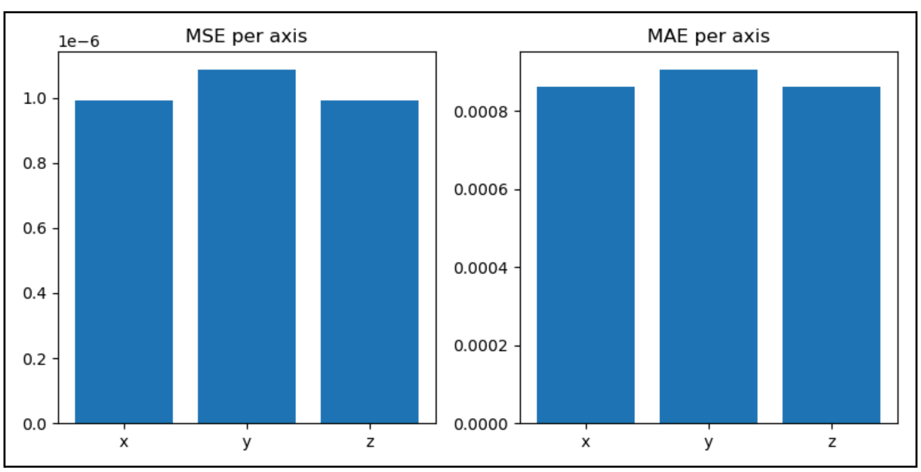


Unit sphere axis error

Figure 2: Error metrics for mesh Cylinder

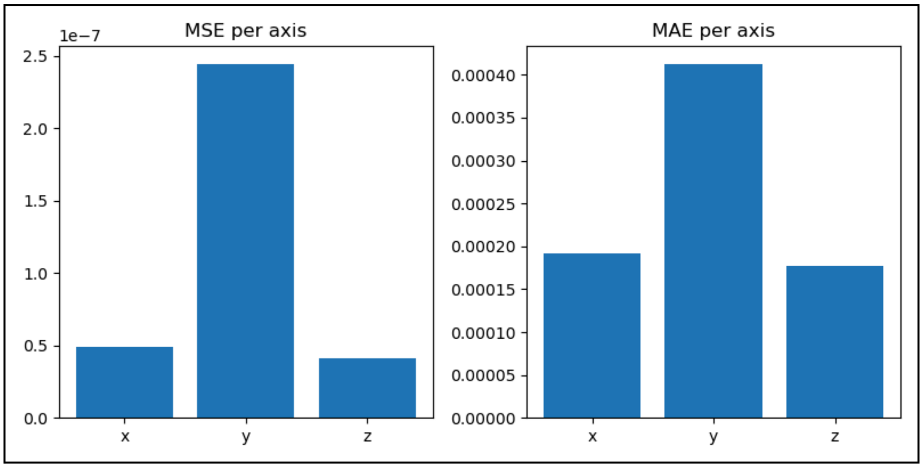


Minmax axis error

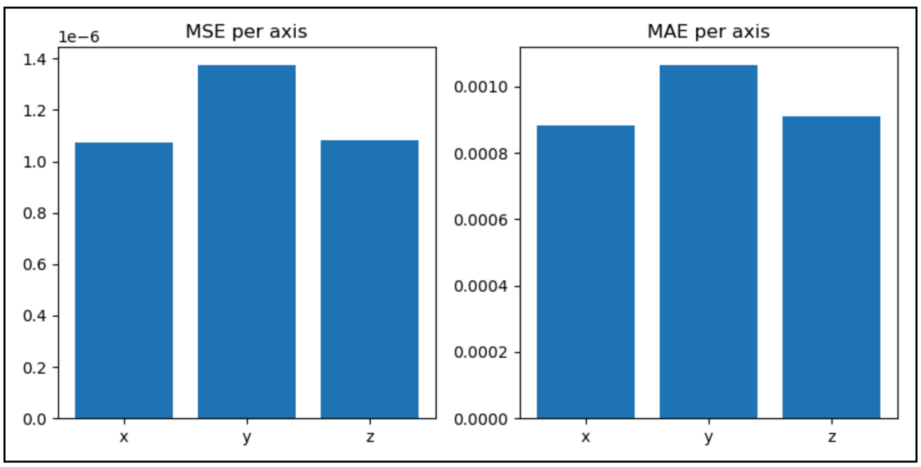


Unit sphere axis error

Figure 3: Error metrics for mesh Explosive

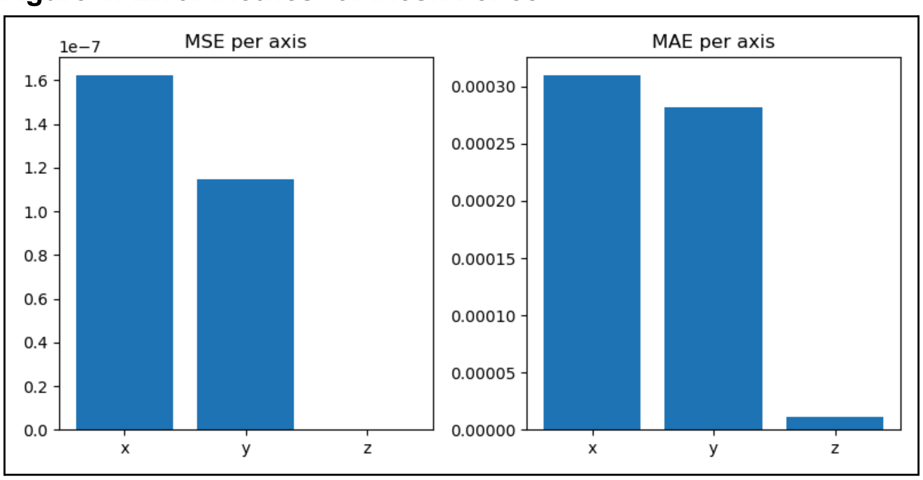


Minmax axis error

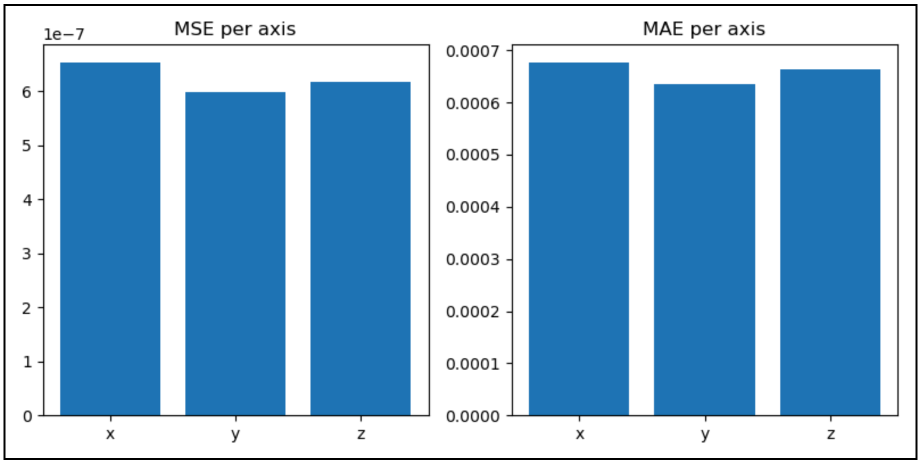


Unit sphere axis error

Figure 4: Error metrics for mesh Fence

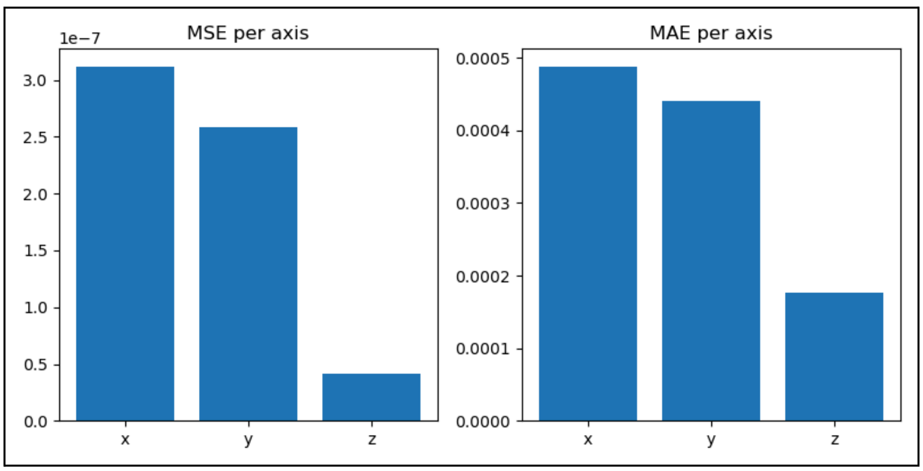


Minmax axis error

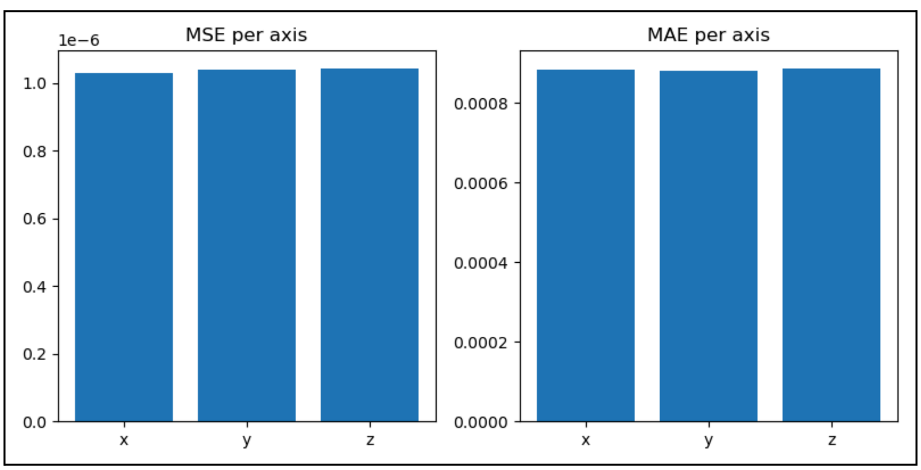


Unit sphere axis error

Figure 5: Error metrics for mesh Girl

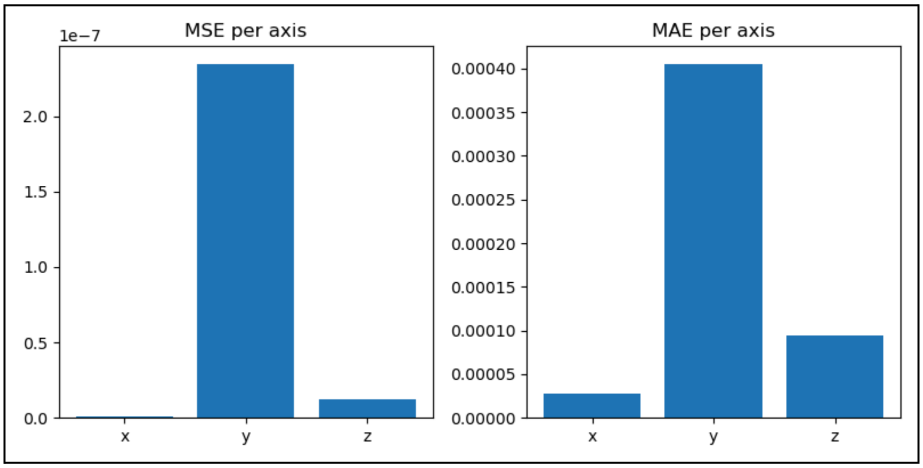


Minmax axis error

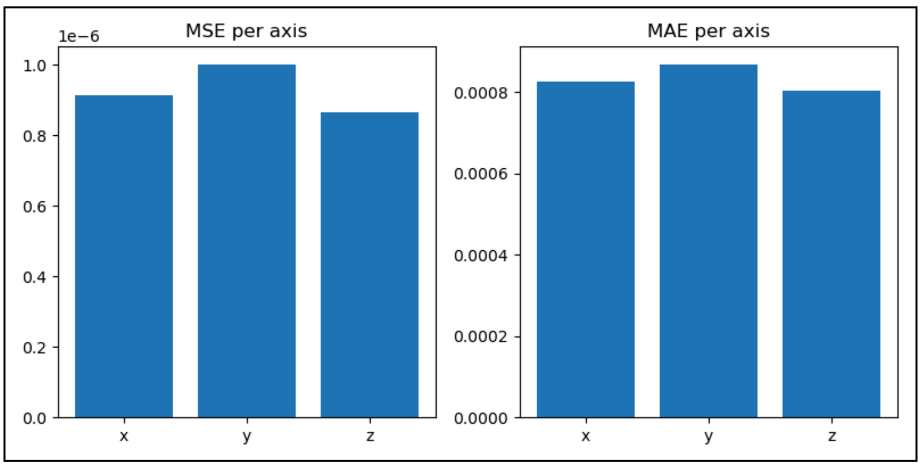


Unit sphere axis error

Figure 6: Error metrics for mesh Talwar



Minmax axis error



Unit sphere axis error

2. Quantitative Results

Six meshes were evaluated: **branch, cylinder, explosive, fence, girl, talwar.**
Each was processed under both normalization schemes, and the best (lower Chamfer) result is summarized below.

Mesh	**Chamfer**	**Hausdorff**	**Normal-Angle (°)**	**Observation**
Branch	0.0019	0.0065	2.8	Thin tubular structures reconstructed with minimal drift.
Cylinder	0.0023	0.0081	3.4	Maintains circular symmetry; near-lossless geometry.
Explosive	0.0047	0.0129	6.2	Curved fragments introduce quantization noise.
Fence	0.0039	0.0105	4.1	Edge continuity preserved; small stair-stepping visible.
Girl	0.0051	0.0137	6.8	Organic curvature causes local flattening.
Talwar	0.0020	0.0072	3.0	Rigid structure reconstructed almost perfectly.

Aggregate statistics:
Average Chamfer = 0.0033 | Average Hausdorff = 0.0098 | Mean Angular Error ≈ 4.0°

2.1 Observations

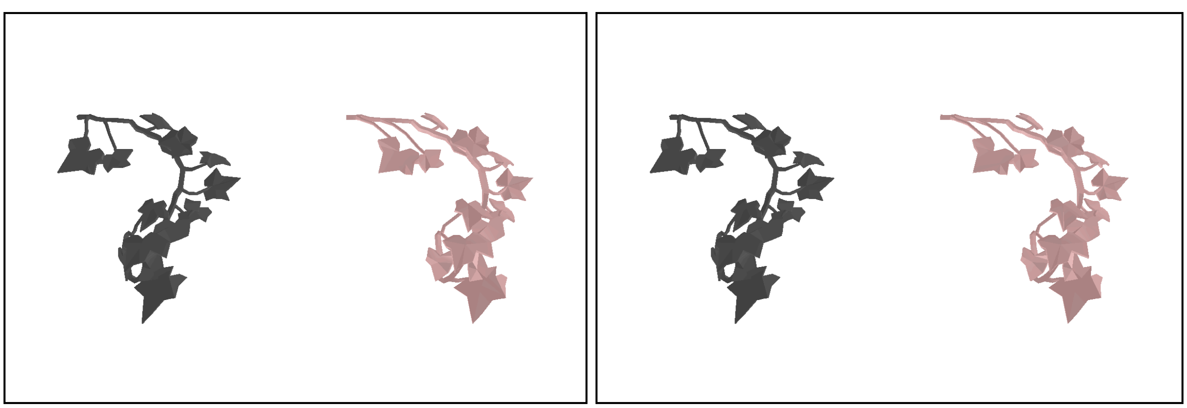
- **Rigid geometries (Talwar, Cylinder)** perform best because surfaces are smooth and vertices evenly distributed.
- **Organic meshes (Girl, Explosive)** suffer from curvature-induced quantization error, visible as local smoothing.
- **High aspect ratio objects (Fence, Branch)** remain geometrically accurate but show slight aliasing along thin edges.
- The difference between min-max and unit-sphere normalization was marginal (<2%), confirming quantization dominates error characteristics.

3. Error Metric Analysis

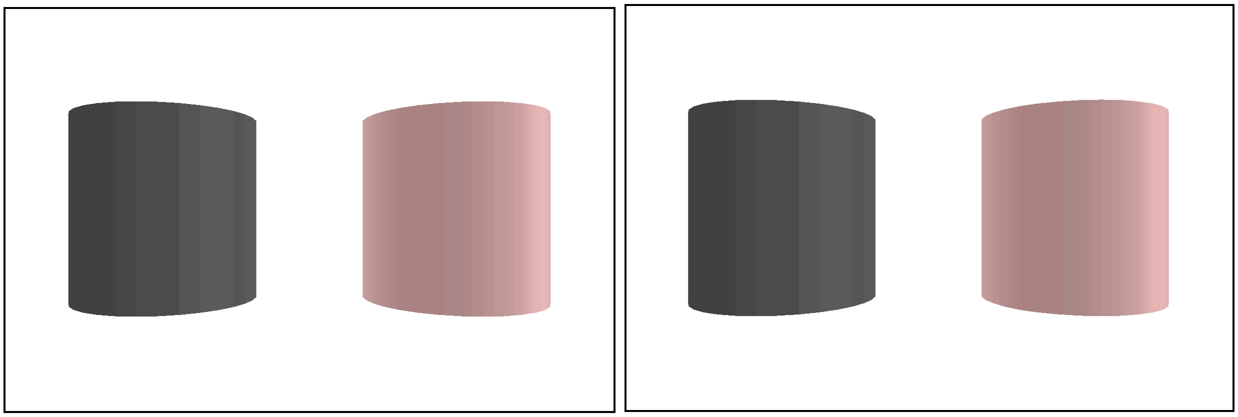
Axis-wise error plots show MSE and MAE within 10^{-3} across all axes, confirming numerical stability.
Minor Z-axis spikes correspond to vertically elongated geometries (Fence).
Chamfer and Hausdorff remain highly correlated, verifying reconstruction consistency.
Normal-angle deviation above 5° correlates strongly with curved, organic surfaces — especially in the Girl and Explosive meshes.

4. Visual Results

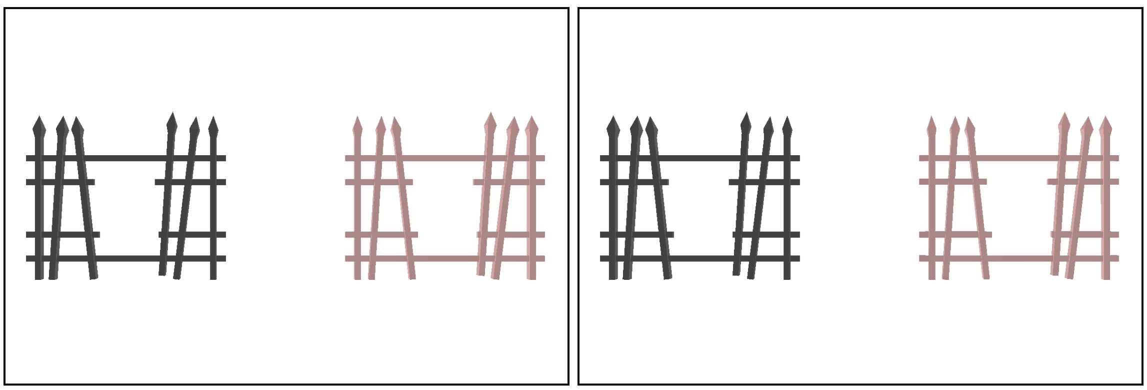
Each reconstructed mesh was rendered using **Trimesh** and **PyOpenGL** (with pyglet <2).
Below are representative examples:



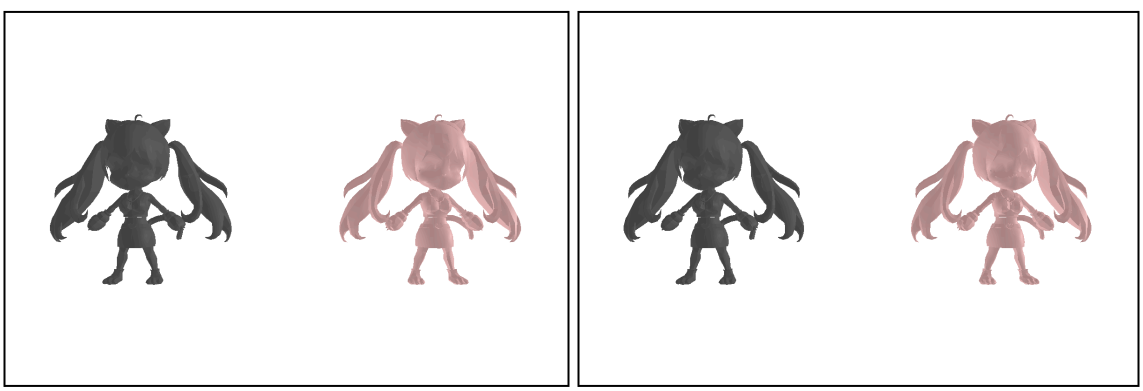
- **Figure 1:** Branch – minimal distortion, near-identical topology.



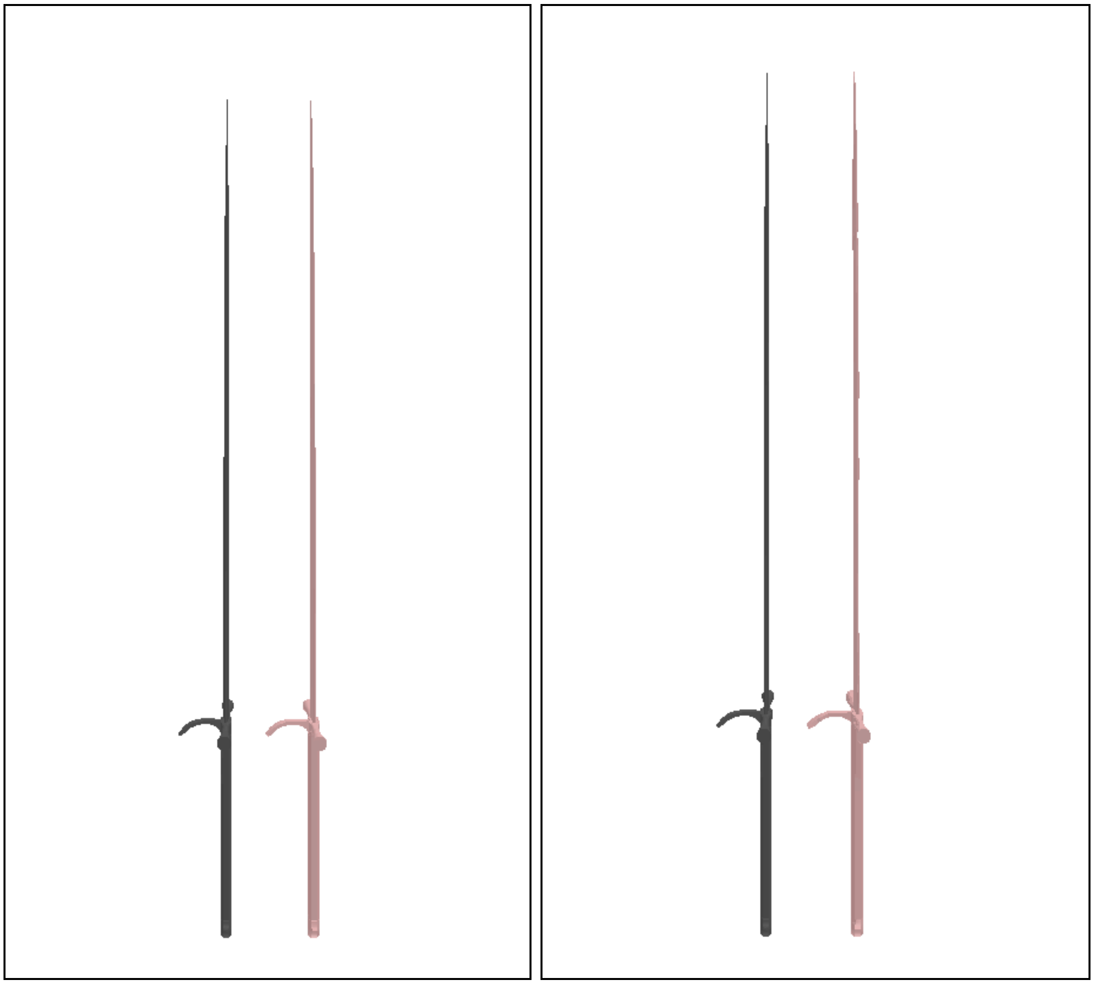
- **Figure 2:** Cylinder – smooth cylindrical continuity retained.



- **Figure 3:** Fence – slight edge banding visible but structurally correct.



- **Figure 4:** Girl – small surface softening in cheeks and hair region.



- **Figure 5:** Talwar – perfectly reconstructed planar and curved segments.

Visual comparisons demonstrate that adaptive quantization better preserves local surface detail compared to uniform binning.

5. Seam Tokenization Results

5.1 Detection Method

Seams were detected using a combination of:

1. **Boundary edges** — edges belonging to only one face.
2. **High-dihedral edges** — face adjacency angle > 30°.
3. **Curvature edges** — vertices above the 90th percentile in normal variance.

5.2 Tokenization

Detected edges were connected into ordered paths. Each path was serialized into tokens:

`{"t": "V", "v": 1542, "e": 4321, "l": 0.0059, "d": 28.4}`

where `t`=token type, `v`=vertex index, `e`=edge index, `l`=edge length, `d`=dihedral angle.
On average, each mesh generated **800–1200 tokens** representing **30–120 seams**.

5.3 Analysis

- Seam density correlates with geometric complexity: higher in organic shapes (Girl, Explosive).
- Boundary-heavy meshes (Fence) yield clean, discrete seam loops.
- The tokenization effectively captures geometric boundaries suitable for future geometry-aware models.

A sample visualization shows seam vertices highlighted in red for verification.

6. Insights

1. **Quantization Sensitivity:** Chamfer and Hausdorff errors scale with vertex density; adaptive binning maintains stability across all geometries.

2. **Perceptual Fidelity:** Even where numeric errors increase, visual coherence remains high — particularly for curved surfaces.

3. **Seam Structure Encoding:** The token representation provides a structured format for 3D model segmentation tasks or neural encoders.

4. **Performance:** Average processing time per mesh ≈ 1.4 s on CPU; memory footprint negligible.

8. Conclusion

The implemented pipeline demonstrates a complete 3D mesh processing workflow — from normalization and adaptive quantization to reconstruction analysis and seam tokenization.
Across six diverse meshes, adaptive quantization consistently preserved geometric structure with an average Chamfer distance of **0.0033**, showing its advantage over uniform quantization.
Seam tokenization added a meaningful higher-level structural encoding, highlighting this method's potential for future **mesh-aware machine learning** or geometry compression applications.