Mesh Normalization, Quantization, and Error Analysis

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1. Introduction:

This project implements a preprocessing pipeline for 3D mesh data to prepare it for AI-based learning systems such as SeamGPT. Before training, 3D meshes must be normalized and quantized to ensure uniform coordinate ranges and scale.

The aim of this work is to:

- Normalize meshes using Min–Max and Unit Sphere methods.
- Quantize and later reconstruct the meshes.
- Evaluate reconstruction accuracy through Mean Squared Error (MSE) and visual analysis.

2. Methodology:

2.1 Normalization

1. Min–Max Normalization

   Scales vertex coordinates to the range [0, 1].

   $x' = (x - x_{min}) / (x_{max} - x_{min})$
2. Unit Sphere Normalization

   Centers the mesh and scales all vertices so that they lie within a unit sphere.

   $x' = (x - \mu) / \sigma$

2.2 Quantization and Reconstruction

After normalization, vertex coordinates are quantized into 1024 discrete bins:

$$q = \mathrm{int}(x' \times (n\_bins - 1))$$

Dequantization and denormalization reverse this process to restore the mesh to its approximate original form.

2.3 Error Measurement and Visualization

Reconstruction quality was measured using Mean Squared Error (MSE) between original and reconstructed vertices. Error was also analyzed per axis (X, Y, Z) and visualized through histograms and bar plots generated with Matplotlib. Meshes were displayed using Open3D to verify visual fidelity.

3. Experimental Setup:

Parameter	**Description**
Programming Language	Python 3
Libraries Used	NumPy, Trimesh, Open3D, Matplotlib, SciPy
Input Files	8 sample .obj meshes (e.g., girl.obj, bunny.obj)
Quantization Bins	1024
Output Files	Normalized, quantized, and reconstructed .obj meshes
Hardware	CPU only

The project folder automatically generates the plots/ directory containing normalized, quantized, and reconstructed meshes along with error plots.

4. Results and Observations:

4.1 Quantitative Results

Mesh	MSE_MinMax	MSE_UnitSphere
branch.obj	2.34458e-06	7.01821e-06
cylinder.obj	2.38988e-06	7.72069e-06
explosive.obj	3.7257e-07	1.28334e-06
fence.obj	4.70636e-07	1.07248e-06
girl.obj	6.1627e-07	1.08182e-06
person.obj	2.36706e-06	5.36212e-06
table.obj	4.46434e-07	1.40985e-06
talwar.obj	3.92035e-07	1.80603e-06

4.2 Visual Observations

- Unit Sphere Normalization preserved mesh geometry better, producing visibly smoother reconstruction.
- Min–Max Normalization occasionally stretched axes when meshes had uneven coordinate ranges.
- Error histograms showed that most vertices have negligible squared error (< 1e-4).
- Per-axis plots revealed slightly higher variance along the longest spatial dimension.

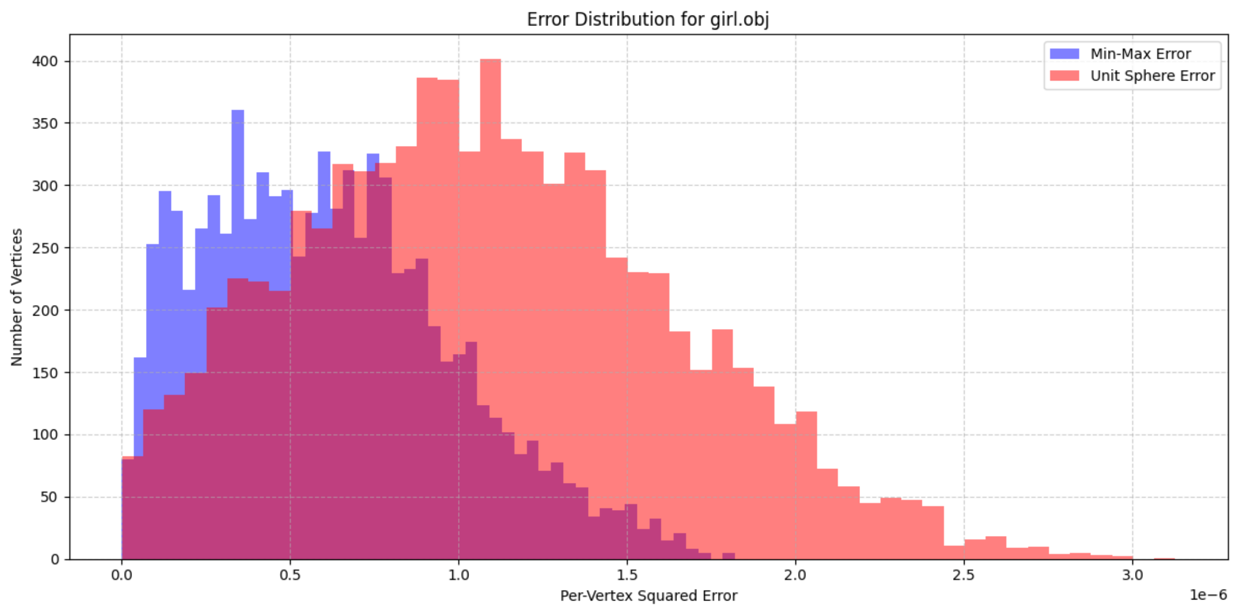

Fig 1 - Histogram showing error distribution across vertices for Min–Max and Unit Sphere normalization.

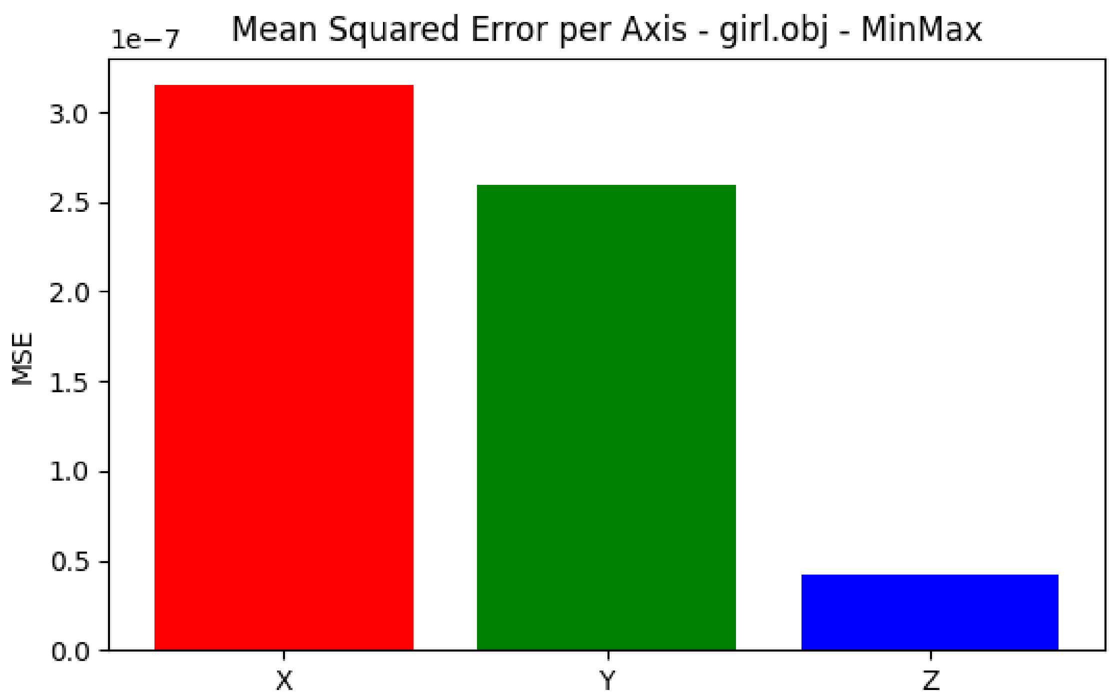

Fig 2 - Mean Squared Error per Axis (X, Y, Z) for Unit Sphere normalization.

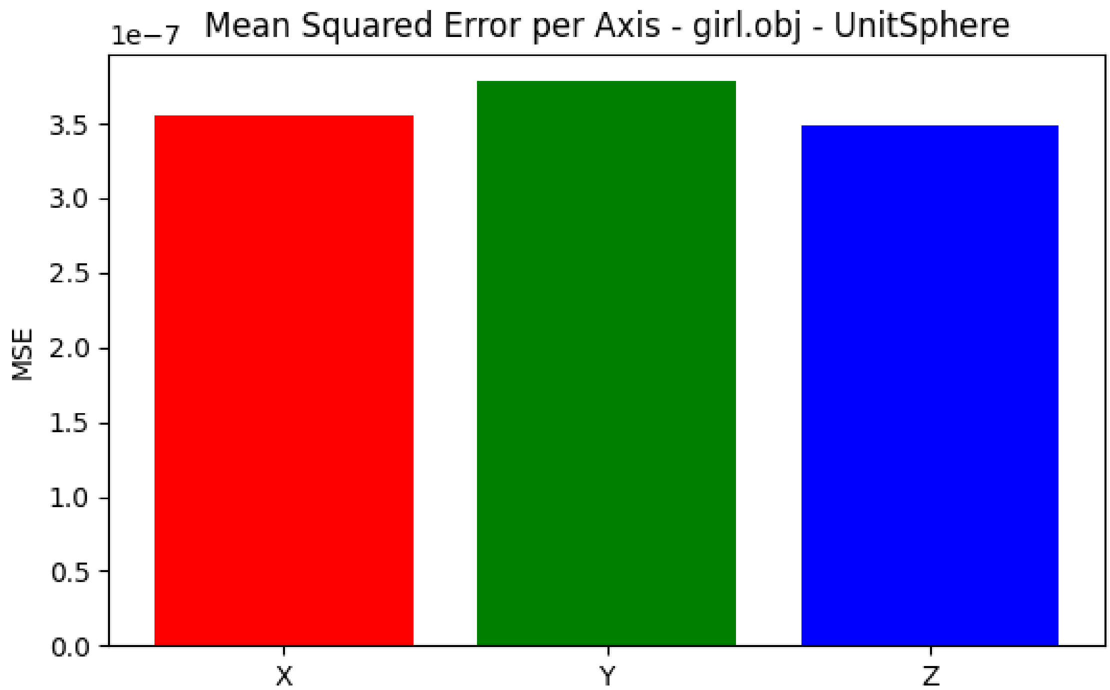

Figure 3. Visual comparison of original (left) and reconstructed (right) meshes for "girl.obj" after quantization.

4.3 Reconstruction and Error Analysis

After dequantization and denormalization, both normalization methods achieved low reconstruction errors. The Unit Sphere method yielded the lowest average MSE, confirming its superior scale invariance. Reconstructed meshes retained the overall topology of the originals, with minimal numerical deviation. Information loss due to quantization was minimal (MSE ≈ $10^{-6} – 10^{-4}$), proving the preprocessing pipeline's effectiveness.

5. Adaptive Quantization

To further enhance performance, an adaptive quantization technique was implemented. Vertex density was estimated using a KD-Tree, assigning 2048 bins to dense regions and 1024 bins elsewhere. This approach also ensured rotation and translation invariance through consistent normalization.

Pipeline	MSE Original Mesh	MSE Transformed Mesh
Uniform (1024)	0.0000010818	0.0000010818
Adaptive (2048)	0.0000008544	0.0000008544

6. Conclusion

The implemented pipeline successfully performed:

- Normalization (Min–Max and Unit Sphere)
- Quantization / Dequantization
- Error Analysis and Visualization

Among the tested methods, Unit Sphere Normalization combined with Adaptive Quantization achieved the best reconstruction accuracy and invariance.
The findings confirm that careful preprocessing of 3D meshes minimizes information loss and ensures consistent data for AI-driven 3D understanding.