Mesh Normalization, Quantization, and Error Analysis Report

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1. Introduction

This report summarizes the end-to-end process of 3D mesh normalization, quantization, reconstruction, and error analysis. The primary goal was to evaluate different normalization and quantization techniques, specifically focusing on rotation and translation invariance and the effectiveness of adaptive quantization compared to uniform quantization.

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2. Methodology

2.1 Mesh Loading and Inspection

The cylinder.obj mesh was loaded using trimesh. Basic statistics including the number of vertices, and min/max/mean/standard deviation of coordinates per axis were extracted and printed.

A fallback mechanism was implemented to create a default cylinder if cylinder.obj was not found.

2.2 Normalization and Quantization (Initial)

Min-Max Normalization: Vertices were scaled to fit within a [0,1] bounding box.

Unit Sphere Normalization: Vertices were centered and scaled to fit within a unit sphere (max distance from origin after centering is 1).

Both normalized meshes were then uniformly quantized using a bin_size of 1024.

Reconstruction was performed by dequantizing and denormalizing the meshes.

2.3 Advanced Challenge: Rotation and Translation Invariance + Adaptive Quantization

Mesh Transformation: A transform_mesh function was developed to apply random rotations and translations to the original mesh. Ten transformed versions were generated.

Invariance Testing: Unit Sphere normalization was applied to the original and all transformed meshes to assess its robustness against rigid transformations.

Adaptive Quantization: Two new functions, adaptive_quantize_vertices_cdf and dequantize_adaptive_vertices_cdf, were implemented. These functions perform and reverse non-uniform quantization based on the empirical Cumulative Distribution Function (CDF) for each axis.

Quantization Comparison: Both uniform (quantize_vertices) and adaptive (adaptive_quantize_vertices_cdf) methods were applied to the original and all transformed normalized meshes, using a bin_size of 1024.

Reconstruction: All uniformly and adaptively quantized meshes were dequantized and denormalized to reconstruct their original scale.

2.4 Error Measurement and Visualization

Error Metrics: Mean Squared Error (MSE) and Mean Absolute Error (MAE) were computed between the original meshes and their reconstructed versions.

Visualization: All meshes (original, normalized, and reconstructed quantized) were visualized using interactive Plotly charts. Error comparisons were also presented via Plotly bar charts.

3. Results and Observations

3.1 Initial Normalization and Quantization Comparison

Min-Max Normalization:

MSE: ~0.00000080

MAE: ~0.00061095

Unit Sphere Normalization:

MSE: ~0.00000058

MAE: ~0.00069121

Observation: Both methods yielded high fidelity reconstructions. Unit Sphere normalization showed a slightly lower MSE, while Min-Max had a slightly lower MAE for the cylinder.obj mesh.

3.2 Rotation and Translation Invariance

Observation: Unit Sphere normalization demonstrated strong invariance to rigid transformations. The MSE and MAE values for uniformly quantized, transformed meshes remained remarkably consistent and low across all 10 randomly transformed versions and the original mesh. This confirms that Unit Sphere normalization successfully isolates the mesh's shape from its pose.

3.3 Uniform vs. Adaptive Quantization Comparison (for Transformed Meshes)

Metric	Quantization Method	Average	Minimum	Maximum
MSE	Uniform	0.00000063	0.00000061	0.00000065
MSE	Adaptive	0.00000422	0.00000319	0.00000596
MAE	Uniform	0.00069121	0.00069121	0.00069121
MAE	Adaptive	0.00118315	0.00091209	0.00139976

Observation: For the cylinder.obj mesh, uniform quantization consistently outperformed the CDF-based adaptive quantization. Uniform quantization resulted in significantly lower MSE and MAE values across all original and transformed meshes. The errors from uniform quantization were also more stable and less variable.

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4. Conclusion

The pipeline successfully demonstrated the principles of mesh normalization and quantization. Unit Sphere normalization proved robust against rigid transformations, maintaining consistent reconstruction quality regardless of the mesh's pose.

While adaptive quantization conceptually aims to reduce information loss by adapting to local density, for the cylinder.obj mesh, uniform quantization provided more robust and accurate reconstruction. This suggests that for meshes with relatively uniform vertex distributions, a simpler uniform binning strategy can be more effective. Adaptive methods might show greater benefits with meshes having highly non-uniform vertex distributions.