Evaluating LiDAR Compression for 3D Semantic Segmentation in Diverse Off-Road Environments on GOOSE Dataset

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Introduction

Transmitting point cloud data is vital for applications like autonomous vehicle navigation, especially when vehicles are compute limited and unable to run large 3d semantic segmentation models locally. LiDAR data easily grows to gigabytes or terabytes uncompressed, making cloud-based model inference or peer to peer vehicle networks costly, especially on low-power devices like drones.

While recent research has advanced point cloud compression, most work evaluates performance using object detection [1] and on urban datasets like SemanticKITTI [7] or nuScenes [8]. These do not reflect performance on off-road outdoor data, which is typically noisier and less structured. We benchmark three LiDAR compressors, RENO [1], TMC13 [9], and LCP [2] at various compression levels on the new GOOSE dataset [5]. We trained two models on this decompressed lidar data to observe their segmentation performance.

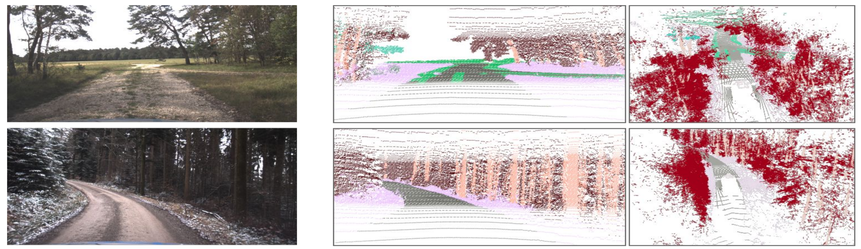
Current Challenges:

- Most Lidar Compressors in literature struggle between achieving competitive compression and real time performance [1]
- Recently compressors have been beginning to achieve this balance but their impact on downstream segmentation tasks remains unexplored [1]
- These compressors are typically neural-based which makes it more uncertain as to how well it can extend to diverse off-road environments [1]

Research Goal:

- Assess the current state of real-time lidar compressors on downstream semantic segmentation tasks for diverse off-road navigation

Methodology

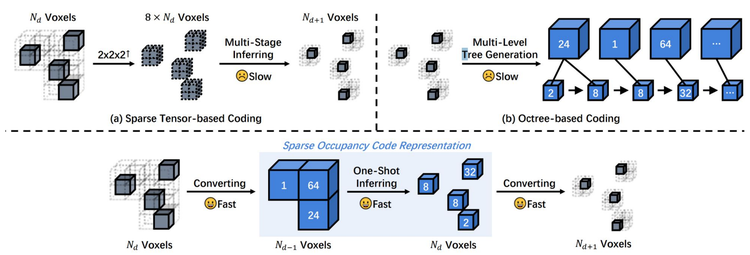


Preprocessing Needed For Semantic Segmentation

1. Convert files to ply with only xyz data (15,000 point clouds total)
2. Quantization (if necessary)
3. Compression + Decompression (including dequantization)
4. Due to point loss, reconnect labels by connecting each point to the closest label from original via K-Nearest Neighbors using a neighborhood of 1
5. Restore intensity values via the same method as step 4 into file to turn it from xyz only to xyz and intensity. Also converts them back into binary files
6. Sphereformer (~25 epochs) and PTV3 (50 epochs) model is trained on this decompressed data with configuration based on GOOSE PTV3 example config from scratch for each compression level. Both were allotted 30 hours and 2 A100s

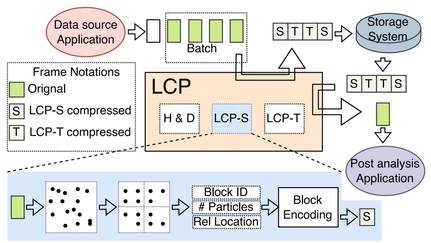
RENO

Skips Octree Building to get occupancy codes for Multiscale Sparse Tensor Based Autoencoder Compression



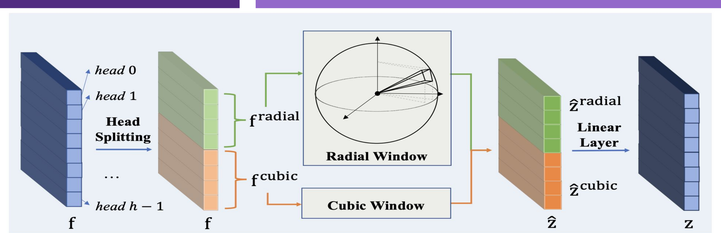
LCP

Built on the FZ Scientific App. Compression Library:
1. Quantization 2. Spatial Blockwise Coding 3. Delta Coding 4. Entropy Coding 5. Dictionary Coding



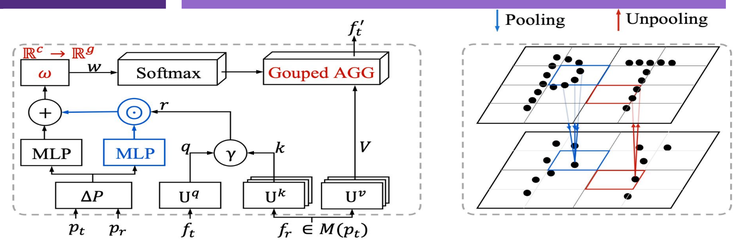
SphereFormer

Uses radial window self-attention to divide space into multiple “windows”

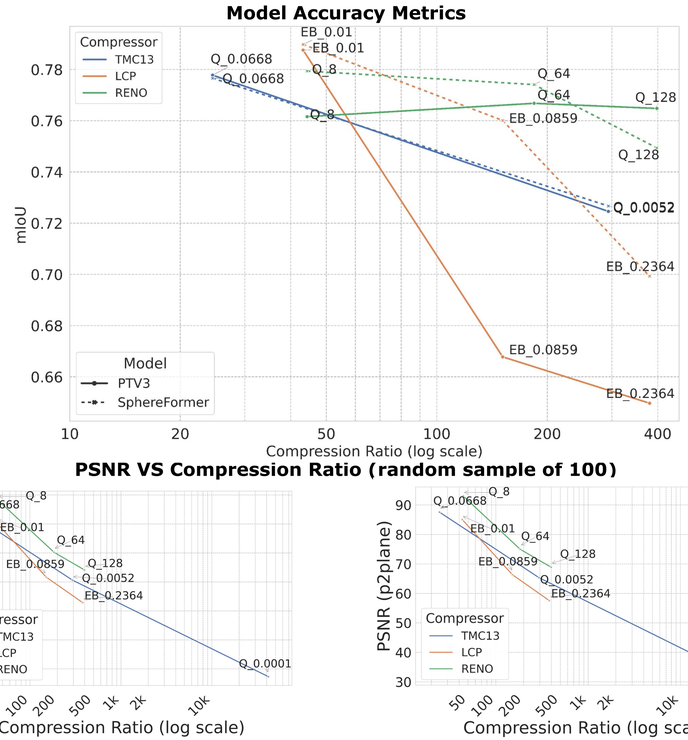


PTV3

Iteration on Point Transformer. Processes points directly and prioritizes scalability



Results / Conclusion



- LCP achieves competitive results to RENO and TMC13 despite never having been used in this domain before. Shows wide disparities across models, maybe due to conflicting with Sphereformer’s windows
- RENO compressor performs the best on downstream semantic segmentation with minimal decay in performance over the levels of compression tested
- TMC13 achieves median to low mIoU compared to LCP and RENO, performing worse or similarly to LCP at similar compression ratios
- Ultimately bolsters neural-based compressors as viable & most performant for diverse off road navigation

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Sources

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