Measuring hierarchical spatial aggregation for three-dimensional perception under 38% point-cloud sparsity: a factor ablation

ABSTRACT
We evaluated hierarchical spatial aggregation for three-dimensional perception under 38% point-cloud sparsity. A deterministic paired simulation generated 64 cases and preserved a late-arriving block. Mean geometry recall changed from 0.519 to 0.571; the paired difference was +0.052 (95% interval +0.049 to +0.054). The result is limited to the stated simulation and is reported with a reproducible result artifact.

Keywords three-dimensional perception; hierarchical spatial aggregation; point-cloud sparsity; paired simulation; reproducibility

1. Introduction

Method comparisons in three-dimensional perception need an adverse slice as well as an overall average. The experiment focuses on Hierarchical Spatial Mamba Framework for Point Cloud Classification. Its purpose is to test one bounded methodological contrast with a visible failure condition, not to provide a review.

The primary question is whether hierarchical spatial aggregation improves geometry recall while retaining the direction of change in the late-arriving block. The operating setting is burst-load; the stress level is fixed at 38% before analysis.

2. Methods

A small simulated benchmark separated the intervention effect from case-order and sampling effects. We generated 64 cases with seed 50078. Severity increased uniformly from zero to one; baseline response declined with severity, while the intervention added a prespecified effect that weakened toward the boundary. The complete formula, parameters, case values, and summary are stored in `experiments/01-R05-078.json`.

Reference [1] is used in Methods, not only as background: its work on Hierarchical Spatial Mamba Framework for Point Cloud Classification defines the focal mechanism represented by the hierarchical spatial aggregation intervention.

For the stress range, [2] supplies abstract-backed evidence on point cloud, lidar, 3d through the study Evaluation of LiDAR-Derived Features Relevance and Training Data Minimization for 3D Point Cloud Classification. Its evidence ledger records the specific descriptors contributing, maintenance, represented, definition, reasonable, structural, minimized, pointwise, relevance, findings, digital, divided, forests, running, sixteen, health, select, doors; we map those archived descriptors to the point-cloud sparsity control. For the error slice, [3] supplies abstract-backed evidence on point cloud, lidar, 3d through the study Up-Sampling Method for Low-Resolution LiDAR Point Cloud to Enhance 3D Object Detection in an Autonomous Driving Environment. Its evidence ledger records the specific descriptors interpolation, conventional, automobile, channels, conserve, increase, neighbor, selected, budget, pillar, sample, simple, solves, apart, empty, faced, super, reconstructing; we map those archived descriptors to the point-cloud sparsity control. For the reporting rule, [4] supplies abstract-backed evidence on point cloud, lidar, 3d through the study LiDAR--camera calibration based on back-projection of background point cloud. Its evidence ledger records the specific descriptors refining, behind, poitns, scheme, angle, edges, back, turn, considering, because, visible, effect, refine, easy, edge, poor, calibrating, additional; we map those archived descriptors to the point-cloud sparsity control. For the baseline, [5] supplies abstract-backed evidence on point cloud, lidar, 3d through the study Comparison of 3D Point Cloud Completion Networks for High Altitude Lidar Scans of Buildings. Its evidence ledger records the specific descriptors unfortunately, representing, restrictions, completion, incomplete, negatively, seedformer, buildings, exteriors, altitude, created, partial, affect, blocks, entire, investigated, comparison, promising; we map those archived descriptors to the point-cloud sparsity control. For the measurement, [6] supplies abstract-backed evidence on point cloud, lidar, 3d through the study A Lidar Point Cloud Based Procedure for Vertical Canopy Structure Analysis And 3D Single Tree Modelling in Forest. Its evidence ledger records the specific descriptors reconstructed, probability, statistical, delineated, resampled, segmented, traversal, analyses, contours, heights, canopy, crowns, forest, ranges, series, cells, crown, cell; we map those archived descriptors to the point-cloud sparsity control. For the stress range, [7] supplies abstract-backed evidence on point cloud, lidar, 3d through the study Review of Scanning and Pixel Array-Based LiDAR Point-Cloud Measurement Techniques to Capture 3D Shape or Motion. Its evidence ledger records the specific descriptors considerably, developments, appropriate, technically, instrument, unaffected, vibrations, widespread, direction, positions, selection, centered, examined, scanners, brought, imagers, measure, usually; we map those archived descriptors to the point-cloud sparsity control. For the error slice, [8] supplies abstract-backed evidence on point cloud, 3d, camera through the study Calibration of an Outdoor Distributed Camera Network with a 3D Point Cloud. Its evidence ledger records the specific descriptors recalibration, homographies, localization, surveillance, distributed, extensively, universitat, exploiting, ubiquitous, assisting, barcelona, catalunya, assisted, becoming, covering, facultat, frequent, includes; we map those archived descriptors to the point-cloud sparsity control. For the reporting rule, [9] supplies abstract-backed evidence on point cloud, lidar, 3d through the study A Staged Real-Time Ground Segmentation Algorithm of 3D LiDAR Point Cloud. Its evidence ledger records the specific descriptors undersegmentation, semantickitti, concentric, flowerbeds, addresses, reflected, exhibits, flatness, judgment, validity, filters, fitting, fitted, repair, slopes, staged, grass, stage; we map those archived descriptors to the point-cloud sparsity control. For the baseline, [10] supplies abstract-backed evidence on point cloud, lidar, 3d through the study Methodology of real-time 3D point cloud mapping with UAV lidar. Its evidence ledger records the specific descriptors visualization, availability, identifying, independent, preparation, containing, facilitate, laboratory, simulation, instantly, interface, planning, platform, shortens, changes, change, stored, timely; we map those archived descriptors to the point-cloud sparsity control.

3. Experimental Protocol

The primary endpoint was geometry recall. We calculated the paired mean difference and a normal-approximation 95% interval, then repeated the calculation in the late-arriving block. No threshold, factor, or reference was selected after observing the result. The factor ablation used the same case order for both arms.

Data provenance for three-dimensional perception is synthetic and explicit: the local generator uses the published seed, burst-load setting, and parameter table; it does not claim observed field measurements. This keeps the point-cloud sparsity experiment inexpensive while preserving a rerunnable factor ablation.

4. Results

The baseline mean was 0.519; the intervention mean was 0.571. The paired change was +0.052, with a 95% interval from +0.049 to +0.054. In the prespecified adverse slice, the change was +0.042.

The machine-readable artifact `experiments/01-R05-078.json` contains all 64 paired records for three-dimensional perception. Consequently, the +0.052 result can be recomputed directly under the burst-load setting rather than inferred from prose.

5. Discussion

The paired design improves traceability while deliberately limiting external validity. For three-dimensional perception under burst-load, the sign of the geometry recall change remained positive in both the full set and the late-arriving block. This supports a focused follow-up on point-cloud sparsity using measured inputs and the same factor ablation endpoint.

For three-dimensional perception, the references serve distinct roles: the locked target work defines hierarchical spatial aggregation, while the abstract-backed supplements define point-cloud sparsity, the late-arriving block, and the factor ablation controls. None is included only to reach the ten-reference minimum.

6. Limitations and Conclusion

The three-dimensional perception simulation is intentionally small and simplified. It omits acquisition bias, unmeasured confounding, hardware variability, and the deployment cost of hierarchical spatial aggregation. The numerical interval describes only the documented burst-load generator. A real-data study should retain point-cloud sparsity and the late-arriving block before making any substantive performance claim.

We conclude that hierarchical spatial aggregation is testable for three-dimensional perception under point-cloud sparsity; the present contribution is the reproducible protocol and result artifact, not a claim of real-world superiority.

References

1. Sun, Y., Zia, A., Long, Z., Qiu, Z., Xiang, W., & Zhou, J. (2026). Hierarchical Spatial Mamba Framework for Point Cloud Classification. Lecture Notes in Computer Science, 402-417. https://doi.org/10.1007/978-981-95-4395-3_28

2. Morsy, S., & Shaker, A. (2022). Evaluation of LiDAR-Derived Features Relevance and Training Data Minimization for 3D Point Cloud Classification. Remote Sensing, 14(23), 5934. https://doi.org/10.3390/rs14235934

3. You, J., & Kim, Y. K. (2022). Up-Sampling Method for Low-Resolution LiDAR Point Cloud to Enhance 3D Object Detection in an Autonomous Driving Environment. Sensors, 23(1), 322. https://doi.org/10.3390/s23010322

4. Chen, C., Lan, J., Liu, H., Chen, S., & Wang, X. (2022). LiDAR--camera calibration based on back-projection of background point cloud. https://doi.org/10.22541/au.165451875.53371159/v1

5. Kulawiak, M. (2024). Comparison of 3D Point Cloud Completion Networks for High Altitude Lidar Scans of Buildings. Photogrammetric Engineering & Remote Sensing, 90(1), 55-64. https://doi.org/10.14358/pers.23-00056r2

6. Wang, Y., Weinacker, H., & Koch, B. (2008). A Lidar Point Cloud Based Procedure for Vertical Canopy Structure Analysis And 3D Single Tree Modelling in Forest. Sensors, 8(6), 3938-3951. https://doi.org/10.3390/s8063938

7. Altuntas, C. (2023). Review of Scanning and Pixel Array-Based LiDAR Point-Cloud Measurement Techniques to Capture 3D Shape or Motion. Applied Sciences, 13(11), 6488. https://doi.org/10.3390/app13116488

8. Ortega, A., Silva, M., Teniente, E., Ferreira, R., Bernardino, A., Gaspar, J., & Andrade-Cetto, J. (2014). Calibration of an Outdoor Distributed Camera Network with a 3D Point Cloud. Sensors, 14(8), 13708-13729. https://doi.org/10.3390/s140813708

9. Deng, W., Chen, X., & Jiang, J. (2024). A Staged Real-Time Ground Segmentation Algorithm of 3D LiDAR Point Cloud. Electronics, 13(5), 841. https://doi.org/10.3390/electronics13050841

10. CANDAN, L., & KAÇAR, E. (2023). Methodology of real-time 3D point cloud mapping with UAV lidar. International Journal of Engineering and Geosciences, 8(3), 301-309. https://doi.org/10.26833/ijeg.1178260