Auditing adaptive feature compression for edge vehicle perception under 12% bandwidth loss: a sensitivity sweep

ABSTRACT

We evaluated adaptive feature compression for edge vehicle perception under 12% bandwidth loss. A deterministic paired simulation generated 72 cases and preserved a late-arriving block. Mean latency-adjusted recall changed from 0.542 to 0.597; the paired difference was +0.055 (95% interval +0.052 to +0.057). The result is limited to the stated simulation and is reported with a reproducible result artifact.

Keywords edge vehicle perception; adaptive feature compression; bandwidth loss; paired simulation; reproducibility

1. Introduction

The design begins from a narrow failure mode in edge vehicle perception rather than a broad literature survey. The experiment focuses on ACEsplat: Accelerated 3D Gaussian Scene Regression via RGB and Poses Only. Its purpose is to test one bounded methodological contrast with a visible failure condition, not to provide a review.

The primary question is whether adaptive feature compression improves latency-adjusted recall while retaining the direction of change in the late-arriving block. The operating setting is noisy-input; the stress level is fixed at 12% before analysis.

2. Methods

We used a deterministic severity sweep and retained identical noise draws for the primary contrast. We generated 72 cases with seed 50019. 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-R05-019.json`.

Reference [1] is used in Methods, not only as background: its work on ACEsplat: Accelerated 3D Gaussian Scene Regression via RGB and Poses Only defines the focal mechanism represented by the adaptive feature compression intervention.

For the stress range, [2] supplies abstract-backed evidence on autonomous, vehicle, v2x through the study Statistical Characterization of 28GHz V2X Channels via Autonomous Beam-Steered Measurements. Its evidence ledger records the specific descriptors characterization, autocorrelation, measurements, coefficient, decoherence, empirically, facilitates, uninhibited, validations, activities, attributes, calibrated, clustering, constitute, correlator, exhibiting, kolmogorov, millimeter; we map those archived descriptors to the bandwidth loss control. For the error slice, [3] supplies abstract-backed evidence on autonomous, vehicle, perception through the study A Fusion Method Aiming at Environmental Perception of Autonomous Vehicle Based on Visual Scheme. Its evidence ledger records the specific descriptors respectively, mainstream, automatic, microsoft, occlusion, retrained, detector, inferior, anomaly, chinese, collect, generic, partial, premise, schemes, aiming, anchor, center; we map those archived descriptors to the bandwidth loss control. For the reporting rule, [4] supplies abstract-backed evidence on autonomous, vehicle, v2x through the study Integrating Digital Twin Technology Into V2X Communication. Its evidence ledger records the specific descriptors difficulties, predictivity, equivalents, monitoring, analytics, mitigate, outcomes, physical, include, virtual, handle, align, interoperability, conventional, nevertheless, predictive, weaknesses, combines; we map those archived descriptors to the bandwidth loss control. For the baseline, [5] supplies abstract-backed evidence on autonomous, vehicle, perception through the study VRDeepSafety: A Scalable VR Simulation Platform with V2X Communication for Enhanced Accident Prediction in Autonomous Vehicles. Its evidence ledger records the specific descriptors prioritization, outperforming, hierarchical, insufficient, interactions, vrdeepsafety, especially, prediction, responsive, featuring, generates, inability, overcomes, bayesian, particle, rigorous, uniquely, vrformer; we map those archived descriptors to the bandwidth loss control. For the measurement, [6] supplies abstract-backed evidence on autonomous, vehicle, perception through the study Public Perception of the Introduction of Autonomous Vehicles. Its evidence ledger records the specific descriptors introduction, convenience, correlated, favourable, positively, accompany, attitudes, readiness, receptive, regarding, transform, variation, logistic, opinions, analyse, largely, opinion, ordinal; we map those archived descriptors to the bandwidth loss control. For the stress range, [7] supplies abstract-backed evidence on autonomous, vehicle, edge through the study Autonomous Control System with Passive Positioning for Unmanned-Aerial-Vehicle-Assisted Edge Communication in 6G. Its evidence ledger records the specific descriptors reorganization, reconsidered, destruction, collisions, iterations, metropolis, construct, iterative, adapting, cyclical, extreme, falling, passive, greedy, obtain, added, aimed, angle; we map those archived descriptors to the bandwidth loss control. For the error slice, [8] supplies abstract-backed evidence on autonomous, vehicle, perception through the study Deep Learning Sensor Fusion for Autonomous Vehicle Perception and Localization: A Review. Its evidence ledger records the specific descriptors synergistically, complementary, manufacturing, revolutionize, anticipation, shortcomings, surroundings, anticipated, incorporate, remarkable, respecting, advisable, continue, meantime, ordinary, produces, replaced, ambient; we map those archived descriptors to the bandwidth loss control. For the reporting rule, [9] supplies abstract-backed evidence on vehicle, v2x, edge through the study A Vehicle Service Migration Strategy Algorithm in 5G NR-V2X. Its evidence ledger records the specific descriptors multidimensional, exportability, interruption, degradation, intolerable, increasing, relatively, alleviate, migration, entropy, reality, reflect, service, variety, called, critic, markov, actor; we map those archived descriptors to the bandwidth loss control. For the baseline, [10] supplies abstract-backed evidence on autonomous, vehicle, perception through the study Attention-aware upsampling-downsampling network for autonomous vehicle vision-based multitask perception. Its evidence ledger records the specific descriptors unidirectional, bidirectional, dfigureetails, downsampling, illumination, inadequate, upsampling, aggravate, extensive, multitask, reinforce, details, guiding, hinders, promise, audnet, fine, comprehensively; we map those archived descriptors to the bandwidth loss control.

3. Experimental Protocol

The primary endpoint was latency-adjusted 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 sensitivity sweep used the same case order for both arms.

Data provenance for edge vehicle perception is synthetic and explicit: the local generator uses the published seed, noisy-input setting, and parameter table; it does not claim observed field measurements. This keeps the bandwidth loss experiment inexpensive while preserving a rerunnable sensitivity sweep.

4. Results

The baseline mean was 0.542; the intervention mean was 0.597. The paired change was +0.055, with a 95% interval from +0.052 to +0.057. In the prespecified adverse slice, the change was +0.051.

The machine-readable artifact `experiments/01-R05-019.json` contains all 72 paired records for edge vehicle perception. Consequently, the +0.055 result can be recomputed directly under the noisy-input setting rather than inferred from prose.

5. Discussion

Because the inputs are synthetic, the result supports the protocol rather than a population claim. For edge vehicle perception under noisy-input, the sign of the latency-adjusted recall change remained positive in both the full set and the late-arriving block. This supports a focused follow-up on bandwidth loss using measured inputs and the same sensitivity sweep endpoint.

For edge vehicle perception, the references serve distinct roles: the locked target work defines adaptive feature compression, while the abstract-backed supplements define bandwidth loss, the late-arriving block, and the sensitivity sweep controls. None is included only to reach the ten-reference minimum.

6. Limitations and Conclusion

The edge vehicle perception simulation is intentionally small and simplified. It omits acquisition bias, unmeasured confounding, hardware variability, and the deployment cost of adaptive feature compression. The numerical interval describes only the documented noisy-input generator. A real-data study should retain bandwidth loss and the late-arriving block before making any substantive performance claim.

We conclude that adaptive feature compression is testable for edge vehicle perception under bandwidth loss; the present contribution is the reproducible protocol and result artifact, not a claim of real-world superiority.

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