Probing adaptive feature compression for edge vehicle perception under 14% bandwidth loss: a error-stratified estimate

ABSTRACT
We evaluated adaptive feature compression for edge vehicle perception under 14% bandwidth loss. A deterministic paired simulation generated 56 cases and preserved a median slice. Mean latency-adjusted recall changed from 0.582 to 0.633; the paired difference was +0.051 (95% interval +0.049 to +0.054). 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

A simple paired experiment provides a low-cost check of adaptive feature compression under bandwidth loss. The experiment focuses on MotiMem: Motion-Aware Approximate Memory for Energy-Efficient Neural Perception in Autonomous Vehicles. 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 median slice. The operating setting is resource-limited; the stress level is fixed at 14% before analysis.

2. Methods

Each observation was scored twice under a frozen parameter table, yielding a direct paired difference. We generated 56 cases with seed 50093. 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-R05-093.json`.

Reference [1] is used in Methods, not only as background: its work on MotiMem: Motion-Aware Approximate Memory for Energy-Efficient Neural Perception in Autonomous Vehicles 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 Optimization of Software Component Allocation for Autonomous Driving in Cloud-Vehicle Edge Environment. Its evidence ledger records the specific descriptors demonstration, computation, constraints, requirement, alleviates, components, redundancy, computers, formulate, optimally, performs, recently, failure, instead, define, board, cope, heterogeneous; we map those archived descriptors to the bandwidth loss control. For the error slice, [3] supplies abstract-backed evidence on autonomous, perception, v2x through the study Edge Intelligence for V2X Communications: Advances in Collaborative Perception and Privacy Preservation. Its evidence ledger records the specific descriptors proliferation, preservation, subsequently, identity, released, already, enabler, leakage, learned, lessons, running, refers, close, rise, systematically, technological, demonstrates, developments; we map those archived descriptors to the bandwidth loss control. For the reporting rule, [4] supplies abstract-backed evidence on autonomous, vehicle, perception through the study Vision and Multimodal Perception for Autonomous Driving: Deep Learning Architectures, Tasks, and Sensor Fusion. Its evidence ledger records the specific descriptors synchronization, revolutionized, transformers, unsupervised, creation, subjects, analyze, explore, modern, regard, fails, full, vits, methodologies, developments, comparative, lightweight, transformer; we map those archived descriptors to the bandwidth loss control. For the baseline, [5] supplies abstract-backed evidence on autonomous, vehicle, v2x through the study 5G and V2X (Vehicle-to-Everything): Road Infrastructure for Level-5 Autonomous Vehicles and Its Application in Peru. Its evidence ledger records the specific descriptors millisecond, connection, foundation, operations, scientific, corridors, logistics, confined, evidence, country, density, drawing, indexed, outline, perfect, rollout, science, slicing; 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 Enhancing Autonomous Vehicle Perception in Adverse Weather: A Multi Objectives Model for Integrated Weather Classification and Object Detection. Its evidence ledger records the specific descriptors augmentation, underscoring, motorcycle, objectives, overlooked, expansion, optimize, advance, cyclist, sensing, nature, severe, gains, sandy, srgan, truck, dawn, four; we map those archived descriptors to the bandwidth loss control. For the stress range, [7] 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 error slice, [8] supplies abstract-backed evidence on autonomous, vehicle, edge through the study Application of Edge Intelligence and Vehicle-To-Vehicle Communication in Next-Generation Autonomous Driving. Its evidence ledger records the specific descriptors calculations, elaborating, exploration, theoretical, electronic, mathematic, processors, summarized, attempted, promising, complete, powerful, profound, strongly, together, onboard, behind, deeper; we map those archived descriptors to the bandwidth loss control. For the reporting rule, [9] supplies abstract-backed evidence on autonomous, vehicle, perception through the study Sensor Perception and Motion Planning for an Autonomous Material Handling Vehicle. Its evidence ledger records the specific descriptors exteroception, transporting, unstructured, simulations, transformed, unexplored, graphical, histogram, hospitals, occupancy, warehouse, material, scanning, simulink, defence, members, toolbox, entire; we map those archived descriptors to the bandwidth loss control. For the baseline, [10] supplies abstract-backed evidence on autonomous, vehicle, v2x through the study Integrating Blockchain and Machine Learning with 6G for Autonomous Vehicle Communication: Achieving Secure, Transparent, and Scalable V2X Networks. Its evidence ledger records the specific descriptors foundational, transparency, bottlenecks, deployments, establishes, evaluations, strengthens, transparent, frameworks, realizing, ensures, synergy, serves, tamper, proof, step, decentralized, necessitates; 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 median slice. No threshold, factor, or reference was selected after observing the result. The error-stratified estimate 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, resource-limited setting, and parameter table; it does not claim observed field measurements. This keeps the bandwidth loss experiment inexpensive while preserving a rerunnable error-stratified estimate.

4. Results

The baseline mean was 0.582; the intervention mean was 0.633. The paired change was +0.051, with a 95% interval from +0.049 to +0.054. In the prespecified adverse slice, the change was +0.044.

The machine-readable artifact `experiments/01-R05-093.json` contains all 56 paired records for edge vehicle perception. Consequently, the +0.051 result can be recomputed directly under the resource-limited setting rather than inferred from prose.

5. Discussion

Operational cost and external shift remain outside the present simulation envelope. For edge vehicle perception under resource-limited, the sign of the latency-adjusted recall change remained positive in both the full set and the median slice. This supports a focused follow-up on bandwidth loss using measured inputs and the same error-stratified estimate 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 median slice, and the error-stratified estimate 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 resource-limited generator. A real-data study should retain bandwidth loss and the median slice 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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