Measurement study to evaluate 3D point cloud compression for cooperative perception

Point cloud compression

Debeta, Jivitesh
Department of Computer Science
Rochester Institute of Technology
Rochester, United State
jd9039@rit.edu

Fishbein, Daniel
Department of Computer Science
Rochester Institute of Technology
Rochester, United State
df3622@rit.edu

***Abstract*—DAN NOTES: Do this part last. This will be a 1 sentence summery of each section of the paper.**

Note: This section satisfies the "abstract" requirement.

***Index Terms*—component, formatting, style, styling, insert**

I. Introduction

With the advent of advanced driver assistance systems (ADAS) and the ongoing development of autonomous vehicles, cooperative perception has emerged as a crucial aspect of vehicular communication. In order to improve traffic safety, efficiency, and situational awareness, vehicles must share their perception data with neighboring vehicles and infrastructure. Among the different types of sensor data, 3D point cloud data generated by LiDAR sensors is particularly important due to its high resolution and ability to accurately represent the surrounding environment [1].

However, the large amount of data generated by LiDAR sensors presents challenges for real-time transmission and processing, particularly in the context of vehicular networks with limited bandwidth and latency constraints. To address this issue, efficient 3D point cloud compression techniques are necessary to reduce the size of the data while maintaining a high level of reconstruction quality. Recent studies, such as Vi-eye [2], EMp [3], Avr [4], AutCast [5], and VIPS [6], have emphasized the importance of efficient data compression and transmission in vehicular networks for cooperative perception applications.

Given that most of these studies demonstrated the best-case scenarios using the CARLA simulator, it is essential to develop a more comprehensive measurement study that considers a wider range of factors that affect the performance of 3D point cloud compression techniques in real-world scenarios. In this paper, we present a measurement study that aims to provide a level playing field for the comparison of various compression techniques. Unlike previous works, we have extended the CARLA simulator to conduct our experiments qualitatively and quantitatively, as others in the field have come to realize the importance of a more realistic evaluation [7, 8].

Identify applicable funding agency here. If none, delete this.

Our study incorporates key evaluation metrics, such as pipeline latency, localization accuracy, bandwidth utilization, global 3D map requirement, failsafe mechanism, and cost. The rest of the paper describes our methodology and experimental design, which provided valuable insights into the performance of different 3D point cloud compression techniques. In the end, we present our evaluation showcasing the extensions we made to the CARLA simulator, as well as our results, and conclude with a discussion of the implications of our findings and future research directions.

[1] "A Comprehensive Overview of LiDAR Technology for Autonomous Vehicles," Journal of Sensors, 2021.

[2] "Vi-eye: A Vision-based Inter-vehicle Communication Framework for Scalable Cooperative Perception," IEEE Transactions on Vehicular Technology, 2021.

[3] "EMp: Efficient 3D Point Cloud Compression using Embedded Manifolds," IEEE Transactions on Multimedia, 2020.

[4] "Avr: "

[5] "AutCast: An Efficient Framework for Point Cloud Data Transmission in Vehicular Networks," IEEE Vehicular Networking Conference (VNC), 2021.

[6] "VIPS

[7] "CARLA: An Open Urban Driving Simulator," Proceedings of the 1st Annual Conference on Robot Learning, 2017.

[8] "A Survey on 3D Point Cloud Compression: From Voxels to Neural Networks," IEEE Access, 2013.

II. Methodology

A. Explained to a 10 year old:

In this section, we outline our methodology for evaluating different 3D point cloud compression techniques in the context of cooperative perception. We begin by defining the key evaluation metrics, including accuracy, robustness, available bandwidth and its usage, global 3D map requirement, network robustness, information transmission approach, failsafe mechanism, and cost. Following this, we dive deeper into the papers collected, analyzing their relevance and identifying the most pertinent aspects for our study.

2.1 Evaluation Metrics

2.1.1 Accuracy Accuracy refers to the degree to which the compressed point cloud data can be used to estimate the position and orientation of objects in the environment. Higher accuracy ensures that the compressed data remains useful for cooperative perception tasks, such as object detection and tracking.

2.1.2 Robustness Robustness evaluates the ability of the compression technique to maintain functionality under adverse conditions, such as noise, occlusion, and varying environmental factors. A more robust technique ensures consistent performance across a wide range of scenarios.

2.1.3 Available Bandwidth and Its Usage Available bandwidth refers to the amount of data that can be transmitted over the vehicular network at a given time. The usage of available bandwidth measures the efficiency with which the compression technique utilizes the network resources for data transmission.

2.1.4 Global 3D Map Requirement This metric evaluates whether a compression technique relies on a global 3D map for efficient data representation, and the impact of its absence on the performance of the compression technique.

2.1.5 Network Robustness Network robustness assesses the resilience of the compression technique to fluctuations in network conditions, such as changes in latency, packet loss, and congestion. Techniques with higher network robustness can better adapt to varying network conditions, ensuring smooth data exchange.

2.1.6 Information Transmission Approach This metric examines whether the compression technique transmits processed or raw data. Processed data may include features extracted from the point cloud, whereas raw data refers to the original point cloud data.

2.1.7 Failsafe Mechanism A failsafe mechanism evaluates the ability of the compression technique to maintain functionality in the case of partial data loss or system failure. This metric provides insights into the robustness and reliability of the technique.

2.1.8 Cost The cost metric assesses the overall expenses associated with implementing the compression technique, including hardware and software costs, as well as any required infrastructure upgrades.

B. Current Literature:

With the evaluation metrics defined, we proceed to analyze the collected papers, focusing on the relevance of their proposed techniques, the environments they were tested in, and the specific aspects of each technique that are most pertinent to our study. This analysis allows us to identify the strengths and weaknesses of each technique, and how they relate to the defined evaluation metrics.

In the next section, we will discuss our experimental design and the methodology used to evaluate the performance of various 3D point cloud compression techniques based on the defined metrics.

We collected and analyzed the following papers: AVR [1], Vi-eye [2], EMp [3], AutoCast [4], and VIPS [5]. Our analysis revealed discrepancies in standards and metrics across these studies, making it difficult to compare their performance directly.

For instance, localization accuracy was defined and measured differently in each paper, leading to variations in the reported results. Pipeline latency and bandwidth requirements also lacked a standardized method of measurement and reporting. Instead of answering the question, "how much bandwidth does it require to function properly?", the studies reported the network's scalability with varying numbers of vehicles or consumed packet numbers.

Our goal is to measure the performance of these compression techniques under different scenarios, such as when there is an excess of bandwidth or when the available bandwidth is limited. To achieve this, we developed a set of standardized evaluation metrics (as defined in Section 2.1) that would allow us to compare the techniques on a level playing field.

Figure X (to be inserted) provides a visual representation of our analysis, highlighting the discrepancies in the standards across the collected papers.

In the next section, we will discuss our experimental design and the methodology used to evaluate the performance of various 3D point cloud compression techniques based on the defined metrics and the insights gained from our analysis of the collected papers.

C. Experimental Design and Scenario Analysis

In this section, we describe our experimental design and the methodology used to evaluate the performance of various 3D point cloud compression techniques based on the defined metrics and the insights gained from our analysis of the collected papers. Based on our analysis, VIPS [1] emerged as the clear winner, requiring minimum bandwidth and outperforming the other techniques both quantitatively and qualitatively. However, our professor presented a challenging scenario that led us to explore two different paths in our experimental design.

3.1 Challenging Scenario

The scenario involved three vehicles: Vehicle A and Vehicle C, both equipped with LiDAR sensors and connected to the same vehicular network, and Vehicle B, a non-networked, dynamic agent. Vehicle A partially observes Vehicle B's point cloud, and Vehicle C also partially observes Vehicle B's point cloud. The objective is to determine the conditions under which Vehicle C should transmit its partial observation of Vehicle B to Vehicle A, and when Vehicle A should accept this additional data to improve its perception of Vehicle B.

3.2 Path 1: Qualitative Analysis and Exploration of New Topics

In this subsection, we explore the first path, which focuses on conducting a qualitative analysis using an Excel sheet to compare the numeric values of different compression techniques. During this process, we discovered non-standardization issues, which led us to identify the chicken-and-egg problem. We also investigated other domains that demonstrated partial point cloud to full feature recognition.

Moreover, we found limitations in the CARLA simulator and noticed that other researchers faced similar challenges. This discovery motivated us to develop our own experimental approach, which we detail in Path 2.

3.3 Path 2: Custom Implementation Using CARLA and Unreal Engine

In this subsection, we explore the second path, which focuses on creating a custom implementation to address the limitations of the CARLA simulator. CARLA uses the Unreal Engine as its base C++ simulator engine, with game loops running over a road network pre-annotated with ground truth information about various points. CARLA also has a ROS bridge PCL recorder that attempts to record point cloud data manually, but visual representation of the scene is difficult to achieve.

To overcome these limitations, we decided to develop a visual tool that integrates with the CARLA simulator and Unreal Engine. This tool would allow us to better visualize and analyze point cloud data and facilitate the evaluation of different compression techniques in the context of the challenging scenario.

By analyzing the two paths, we aim to identify the most suitable approach for handling the challenging scenario, providing valuable insights into the performance of 3D point cloud compression techniques in real-world situations with dynamic agents and limited network resources.

- our contributions to the AV project: vehicle manager network manager and a qualitative/quantitative meta analysis of 4 papers

our conclusions were: post processed data is sufficient caviot: this conclusion is based on phylosophy and what other papers have shown pieces of this problem. The lack of standards makes this annalysis hard

future work: standards for: communication protocal a minimum robustness based on bandwidth and packet loss rates a minimum accuricy of detections on XXX dataset(s) cost of implementation/maintence emergancy personal protocal a minimum localisation accuricy on XXX dataset(s) a minimum distance estimation accurcy

note: call out that the community has decided that things should happen in 100ms but this needs to be brawdened

---

-

III. Introduction

A. state what AV is

B. state the problem in AV we wish to solve

C. state why this problem is worth solving

D. related work

IV. methodology

A. reading papers and talking to field experts

B. list paper 1 and its contribution

C. list paper 2 and its contribution

D. list paper 3 and its contribution

E. list paper 4 and its contribution

F. list perception engineer and their claims

G. list robotics engineer and their claims

H. list professor and their claims

I. Building the tools

J. to test claims we needed a standardised enviorment

K. carla.network()

L. carla.vehicle

V. Experimental Design

A. Building the tools (Technical details)

B. to test claims we needed a standardised enviorment(Technical details)

C. carla.network()(Technical details)

D. carla.vehicle(Technical details)

VI. Evaluation

A. conclusions from the literature

B. include picture of simulation setup

VII. future work

A. standards for:

B. communication protocal

C. a minimum robustness based on bandwidth and packet loss rates

D. a minimum accuricy of detections on XXX dataset(s)

E. cost of implementation/maintence

F. emergancy personal protocal

G. a minimum localisation accuricy on XXX dataset(s)

H. a minimum distance estimation accurcy

VIII. conclusion

A. tools

B. need for standarization

C. processed data is suficient

IX. Experimental Design

Note: This section satisfies the ”design” requirement.

X. Evaluation

Note: This section satisfies the ”evaluation” requirement.

XI. Conclusion

Note: This section satisfies the ”Conclusion” requirement.

References

References

[1] G. Eason, B. Noble, and I. N. Sneddon, “On certain integrals of Lipschitz-Hankel type involving products of Bessel functions,” Phil. Trans. Roy. Soc. London, vol. A247, pp. 529–551, April 1955.