Cross-Layer Feasibility Study of AV Teleoperations on 5G Networks

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ABSTRACT

Remote driving or teleoperating autonomous vehicles (AVs) represents a key use case targeted by emerging 5G networks. This study investigates the feasibility and performance of autonomous vehicle (AV) teleoperation over 5G networks. Through cross-layer analysis and end-to-end evaluations, we assess the impact of various factors on streaming performance and latency. Novel per-frame Quality of Experience (QoE) metrics are introduced to quantify visual quality deviation, providing granular insights into streaming quality. The study also examines the effects of compression techniques and adaptive bitrate strategies on latency and visual quality. Additionally, the influence of 5G Radio Access Network (RAN) factors on latency is explored, highlighting key considerations for optimizing teleoperation performance. Furthermore, end-system mechanisms for enhancing tail latency are investigated, contributing to the development of robust AV teleoperation systems on 5G networks.

KEYWORDS

5G, Low Latency, Autonomous Vehicles, Teleoperation, AI

1 INTRODUCTION

Autonomous Vehicles (AVs) have progressed significantly since the 2005 DARPA Challenge, with Tesla, Waymo, Uber, and Cruise achieving Level-4 autonomy [2, 5–7]. However, Level-5 autonomy, where vehicles operate without human intervention, remains challenging. AV teleoperation emerges as a crucial step towards this goal.

The potential of 5G technology for AV teleoperation is promising [1, 3, 4], yet its network requirements are unclear. Safety is critical, demanding low latency and high bandwidth for teleoperation. However, current 5G networks suffer from downlink/uplink bandwidth asymmetry.

This study explores the feasibility of AV teleoperation on 5G networks, aiming to understand the challenges and opportunities for enhancing safety and efficiency in autonomous transportation.

Contributions: In our study, we conducted a thorough analysis of AV teleoperation feasibility on 5G, employing cross-layer and end-to-end approaches. We introduced per-frame QoE metrics to assess visual quality deviation and examined the impact of compression and adaptive bitrate techniques on latency and visual quality. Additionally, we investigated the influence of 5G RAN factors on latency and explored end-system mechanisms for enhancing tail latency.

2 BACKGROUND

AV Sensors & Data Requirements: The MnCAV vehicle integrates a suite of advanced sensors, including RGB cameras, thermal cameras, LiDAR, radar, GPS/ GNSS, IMU, and odometry. Notably, LiDAR data predominates, comprising 79% of the sensory input, followed by video data at 17.2%, with other sensor data making up the remaining <4%. This comprehensive sensor fusion enables precise and safe navigation in diverse environments.

5G Performance: The challenge for teleoperations lies in the inherent asymmetry between 5G downlink (DL) and uplink (UL) throughput. The average DL throughput for AT&T, T-Mobile, and Verizon are 217 Mbps, 571 Mbps, and 370 Mbps, respectively, while the corresponding average UL throughput values are 47 Mbps, 72 Mbps, and 67 Mbps. While 5G DL physical layer (PHY) throughput is notably higher than UL PHY throughput, the teleoperation process demands more bandwidth in the uplink direction. Transmitting data from cameras and LiDAR sensors in the uplink requires greater bandwidth compared to the relatively lighter control commands sent to the AV in the downlink.

3 EXPERIMENT SETUP & DATASET

On the vehicle side, the sender application subscribes to ROS topics for video and LiDAR data, compresses it, and streams it to the server. The server, hosted on an AWS instance, operates a receiver application for teleoperation, establishing connectivity with the vehicle through an SSH tunnel. To facilitate efficient video streaming, the system employs RTSP and DASH-based LoL^{+} protocols, while LiDAR data transmission is managed through TCP/UDP socket programming. The teleoperation system streams prerecorded video and LiDAR data collected from a cross-state driving campaign. We stream data through various driving routes across different city environments.

We introduce the following QoE metrics to quantify uplink video/LiDAR data sensor streaming performance:

- **Per-frame total delay**: Time from frame generation to complete reception and readiness for playback at the receiving side.
- **Per-frame network delay**: Time from the first packet transmission to the last packet reception at the receiving side.
- **Video quality**: Assessed using standard metrics like PSNR and SSIM.
- **Perceptual quality deviation**: Measures the difference in SSIM values between expected and actual frames at playback time.

4 RESULTS

Application Layer: In the analysis of application layer Quality of Experience(QoE) results, two scenarios of single MJPEG video streaming were evaluated: one using RTSP and the other utilizing LoL^{+}. For the RTSP scenario, it was observed that the distribution of per-frame network delay exhibited a long-tailed pattern, with approximately 25% of frames experiencing delays exceeding 100 ms. Additionally, the cumulative delay effect was evident, as total delay accumulated from past queueing delays. Moreover, it was found that this cumulative delay had a proportional impact on perceptual quality, underscoring the importance of managing delay for maintaining video quality. In the case of LoL^{+} video streaming, it was noted that while latency performance gains were achieved, they came at the cost of reduced video quality. This highlights the trade-off between latency and video resolution adaptation, emphasizing the need for balancing these factors to optimize streaming performance.

Impact of 5G RAN on AV Teleoperation: The impact of 5G RAN factors on AV teleoperation, specifically per-frame network delay, was investigated. Analysis revealed that delay increases significantly with higher Block Error Rate (BLER), rising by 155% when transitioning from 0-5% BLER to 10+% BLER. Similarly, delay also showed a substantial increase, by 48%, from low to high Channel Quality Indicator (CQI) levels. These findings underscore the critical influence of 5G RAN parameters on the latency experienced in AV teleoperation, highlighting the importance of optimizing lower-layer network conditions for seamless operation.

5 CONCLUSION

In summary, this study explores the feasibility of teleoperating autonomous vehicles (AVs) over 5G networks. Through thorough analysis and evaluations, we assess factors impacting streaming performance and latency. Introduction of novel per-frame Quality of Experience (QoE) metrics provides insights into streaming quality, while exploring effects of compression techniques and adaptive bitrate strategies on latency and visual quality. Analysis of 5G Radio Access Network (RAN) factors highlights optimization considerations, and investigation into end-system mechanisms aims to enhance tail latency for robust AV teleoperation on 5G networks.

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