Towards a Simulation Framework for Performance Evaluation of RIS-Assisted Collective Perception Message Exchange

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***Abstract*—Cooperative, connected and automated mobility (CCAM) is revolutionizing the future of transportation by promising substantial improvements in road safety, traffic efficiency, and driver comfort. Central to CCAM is the concept of collective perception, where vehicles exchange sensor data via vehicle-to-everything (V2X) communication to overcome individual perception limitations. However, communication disruptions, data privacy, and reliability issues persist, particularly when obstacles interfere with the exchange of collective perception messages (CPMs). This paper investigates the potential of reconfigurable intelligent surface (RIS) in addressing these challenges by enhancing V2X communication channels. For the first time, we explore the integration of RIS in a simulation framework designed to model the exchange of CPM messages in cooperative driving environments. Additionally, we perform object detection on a static vehicle's field of view and transmit the video stream with detection results to a moving vehicle, further enhancing situational awareness. We also present a novel analysis of the trade-off between cooperative perception quality and latency under RIS-assisted communication by evaluating the impact of frame compression on packet loss and information freshness. Using the CoopeRIS platform integrated with CARLA, we demonstrate how RIS-assisted communication can mitigate the impact of obstacles and improve the reliability of CPM exchange, providing a robust foundation for the future of collective perception services in CCAM. Our results show significant gains in communication reliability, detection precision, and the effectiveness of CPM exchange in obstructed environments.**

***Index Terms*—Collective perception, CoopeRIS, Veins, Reconfigurable intelligent surfaces, RIS-assisted communication, Object detection, Age of information, Packet loss, End-to-end delay**

I. Introduction

The emergence of cooperative, connected, and automated mobility has the potential to reshape transportation systems worldwide, offering benefits such as improved road safety, reduced traffic congestion, and enhanced driving comfort. At the heart of cooperative, connected and automated mobility (CCAM) lies the ability for vehicles and infrastructure to collaborate, sharing real-time sensory data to achieve a collective understanding of the surrounding environment [1]. This concept, widely referred to as collective perception, plays a critical role in extending the sensing capabilities of individual vehicles beyond their onboard sensors, enabling them to detect and anticipate potential hazards that would otherwise remain outside their field of view. Such capabilities are particularly important in autonomous driving, where vehicles rely on a combination of advanced perception, planning, and control systems to navigate safely and efficiently in complex traffic scenarios [2]. By leveraging cooperative perception, autonomous systems can make more informed decisions, leading to safer maneuvers, smoother traffic flow, and improved adaptability to challenging urban driving conditions.

While individual perception systems in autonomous vehicles have made significant advancements, they still face limitations due to sensor occlusions, noise, and environmental factors [3], [4]. To address these challenges, collective perception relies on vehicle-to-everything (V2X) communication, enabling vehicles to exchange critical information, such as cooperative awareness messages (CAMs), collective perception messages (CPMs), and maneuver coordination messages (MCMs) [5]. The adoption of these technologies is expected to improve situational awareness, but is still impeded by several factors, including communication disruptions, data privacy concerns, security vulnerabilities, and the integration of high-frequency communication signals, such as millimeter wave (mmWave) and terahertz (THz) bands [6].

Recent research has made strides in enhancing V2X communication networks, yet challenges persist, particularly in the face of obstacles that obstruct the line-of-sight communication links between vehicles [7], [8]. This problem becomes even more pronounced when high-frequency signals are used, as they are more susceptible to attenuation and blockage. In this context, reconfigurable intelligent surface (RIS) have emerged as a promising and cost-effective technology to enhance communication reliability by dynamically altering the wireless propagation environment and enabling more favorable signal paths. Despite its potential, the integration of RIS into CCAM systems and its influence on the seamless exchange of CPMs among cooperative vehicles has not yet been explored in depth,

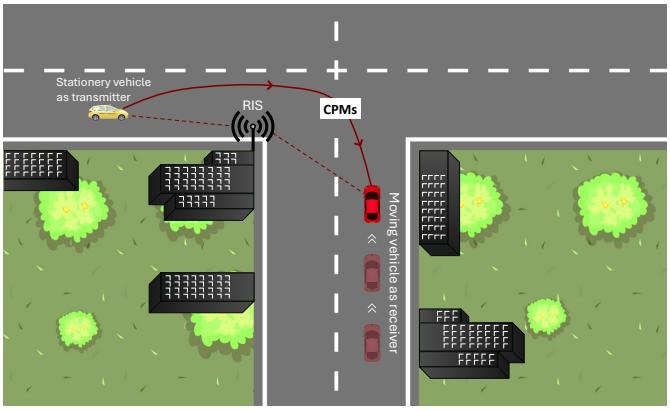


Fig. 1: Simulation scenario.

TABLE I: Simulation Parameters

Parameter	Value
Path loss model	Free space ($\alpha = 2.0$), with product of distances [9]
Shadowing model	Simple obstacle shadowing
Operating frequency	25 GHz (mmWave)
Transmission power	30 dBm
Antenna gain	29 dBi
Coding states (N_s)	8
Size of RIS in multiples of λ	20λ
Elements per λ (ρ_z)	2
Angular resolutions d_ϕ, d_θ	1°
Receiver distance to intersection	60 m

leaving an important research gap in the development of robust CCAM communication frameworks.

In this paper, we aim to bridge this gap by introducing a novel simulation framework that incorporates RIS-assisted communication into the context of collective perception. We leverage the CoopeRIS platform, which allows for the simulation of RIS in cooperative driving environments, and integrate it with CARLA and SUMO to facilitate CPM exchange between vehicles. Additionally, we perform object detection on the output of the camera sensor of the stationary vehicle and transmit the video stream with object detection results to the moving vehicle, adding to the overall situational awareness. A key contribution of this work is the introduction of age of information (AoI) as a critical performance metric to assess the freshness and timeliness of cooperative perception data under RIS-assisted communication. Through this integration, we investigate the benefits of RIS in mitigating communication disruptions caused by obstacles and demonstrate how RIS can enhance the reliability of collective perception services. Our findings contribute to the understanding of RIS in autonomous driving systems and offer valuable insights into the future of CCAM technologies.

II. Simulation Scenario and Framework

In our simulation scenario, we consider two vehicles: a static car and a moving car approaching a T-intersection. At the intersection, we position a RIS at a height of 5 m, with its placement optimized to maximize signal reflection and coverage. The static car is located 60 m away from the RIS, while the moving car advances uphill towards the intersection at a constant speed of 48 km/h. The stationary car is set to transmit data at a rate of 12 packets per second to the moving car. Obstructions in the environment, such as buildings, intermittently block the line of sight between the moving car and the static car. As a result, the moving car becomes visible to the static car for only a few seconds during its movement before being obscured again. This setup, illustrated in Fig. 1, allows us to study the impact of RIS on the reliability of CPM exchange in CCAM environments.

To implement and evaluate this scenario, we propose a comprehensive framework that integrates multiple simulation tools to model V2X communication dynamics, RIS-environment interactions, and CPM exchange. The framework leverages the CoopeRIS platform [9], designed for RIS-enhanced V2X communication, combined with CARLA and SUMO to create a dynamic driving environment. Additionally, we employ YOLOv7, a state-of-the-art deep learning model, for object detection on the moving vehicle's field of view. This improves situational awareness, enabling the transmission of video streams with detection results to the moving vehicle.

A. CoopeRIS Platform

The foundation of our simulation framework is the CoopeRIS platform, which is built upon the Plexe, Veins, SUMO, and OMNeT++ ecosystem. CoopeRIS is designed to model RIS-enhanced mmWave communication within CCAM environments, allowing simulation of RIS effects on V2X communication channels [9]. The platform provides a comprehensive environment for evaluating the performance of RIS-assisted communication by enabling realistic modeling of both the physical layer and the communication processes involved in vehicle-to-vehicle (V2V) interactions. The key parameters of the scenario are summarized in Tab. I.

1) RIS Functionality in CoopeRIS: In the proposed simulation framework, vehicles are equipped with standard transceivers, while RIS elements are strategically placed to improve communication between vehicles. RIS modules reflect and retransmit signals, improving the signal gain by focusing the signal towards the receiver helping to overcome obstructions such as buildings. From an implementation point of view, RISs annotate the reflected signals with metadata, such as incidence angles, to calculate gains at each hop. The framework also prevents infinite reflections, avoiding signal degradation and reducing computational overhead.

2) RIS Gain Modeling: One of the critical aspects of integrating RIS into our simulation is the ability to model the gain introduced by RIS elements at each hop in the communication chain. This gain depends on the angles of incidence and reflection, which vary based on RIS configuration and vehicle

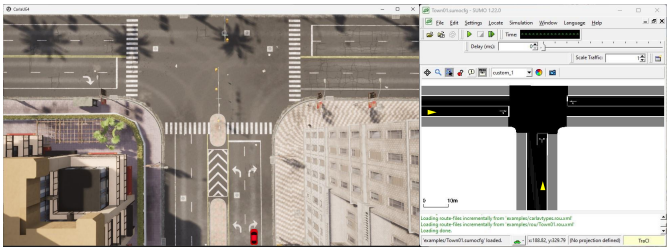


Fig. 2: An instance from CARLA-SUMO co-simulation representing a V2V communication scenario.

positioning, and the configuration of the RIS. By changing the phase of the reflected signal on every element, the RIS focuses the signal towards a specific direction, and the model can precisely derive the signal gain. This ensures that the simulated V2X communication links are accurately adjusted for the contributions of RIS elements, allowing realistic assessments of communication reliability. For the sake of brevity we omit the details of the model, which are clearly explained in the original paper [9].

3) Integration with Communication Layers: CoopeRIS implements both the medium access control (MAC) and physical layer (PHY) of the communication system. The PHY layer of RIS elements manages signal reflection, retransmission, and power adjustment, ensuring that reflected signals compensate for path loss and prior RIS gains. While the MAC layer of standard transceivers manages data encapsulation, encoding, and modulation, it does not handle channel access protocols in this framework. Instead, its focus is on data transmission across the V2X network, while the PHY layer of RIS elements handles the reflection and optimization of the signals.

Together, these components ensure a seamless integration of RIS elements within the V2X communication network, enabling reliable CPM exchange even in challenging environments.

B. Integration with CARLA and SUMO

To model the dynamic nature of cooperative driving environments, we integrate CoopeRIS with CARLA and SUMO. These platforms collectively provide a realistic real-time simulation of vehicle mobility and traffic dynamics [10], [11], enabling the evaluation of RIS-enhanced communication in real-world driving scenarios. A communication scenario is illustrated in Fig. 2, showing a snapshot of the CARLA-SUMO integration. By coupling these simulations with CoopeRIS, we study how RIS enhances communication reliability in diverse traffic conditions and obstacle layouts.

1) CARLA Simulator: The CARLA simulator, a high-fidelity open-source platform, models autonomous driving scenarios with realistic vehicle dynamics, sensor models, and environmental conditions. In our framework, CARLA simulates the physical movement and sensor interactions of vehicles in urban and highway environments. Its integration with CoopeRIS enables modeling of vehicle-RIS interactions

Fig. 3: An instance of real-time object detection.

within dynamic environments, where vehicle positions and behaviors continuously evolve. Vehicles in CARLA are equipped with sensors such as cameras, radars, and LiDARs to detect obstacles, pedestrians, and other vehicles. The sensor data generated are used to create and exchange CPMs, forming the basis of collective perception in CCAM systems.

2) SUMO Simulator: The SUMO (Simulation of Urban MObility) tool is used to model traffic flow in large-scale road networks. By integrating SUMO with CARLA, we can simulate realistic traffic mobility patterns and vehicle interactions at both the macroscopic (traffic flow) and microscopic (vehicle-specific) levels. This enables synchronized simulation of complex driving scenarios where multiple vehicles, pedestrians, and infrastructure components interact simultaneously.

C. Object Detection Using YOLOv7

To further enhance the collective perception capabilities of the system, we integrate object detection into the static vehicle's sensor suite. For its high precision and real-time processing capabilities, we employ the object detection model YOLOv7 [12]. As a single-stage object detection framework, YOLOv7 analyzes the entire image in one forward pass, making it particularly efficient for time-sensitive applications. To investigate the trade-off between computational efficiency and detection accuracy, we evaluate two variants of YOLOv7: the lightweight and compact tiny model with 6M trainable parameters and the more complex large model containing 151.7M trainable parameters. Fig. 3 demonstrates an instance of this real-time object detection system, displaying a representative snapshot captured during the evaluation process within the simulator environment.

D. Simulation Process and CPM Exchange

The simulation process involves several key steps. First, we deploy vehicles in the simulation environment, equipped with standard V2X transceivers and operating within a predefined route generated by SUMO. At the transmitter side, the static vehicle performs object detection on high-resolution camera

frames using a pre-trained detection model. The detected object information, including bounding boxes, class labels, and confidence scores, is retained for transmission, while the raw camera frame is compressed to a lower resolution (96×96) to reduce data size. As vehicles move through the environment, obstacles such as buildings, may obstruct the line of sight between communication links, causing signal degradation. When communication degradation occurs, CoopeRIS dynamically configures RIS elements to reflect signals and optimize the transmission, mitigating the effects of these obstacles.

During the CPM exchange, which contains compressed raw frames and additional metadata such as vehicle positions, velocities, and detected object frames including their bounding boxes, class labels, and confidence scores, CoopeRIS ensures that the communication links remain reliable by adjusting the RIS configuration in real-time. The CPMs are broadcast as single $12\,\mathrm{kB}$ packets, since there is no unicast feedback implemented and splitting the data into multiple packets would become complex and would require an application-level recovery mechanism. The moving vehicle receives CPMs from the stationary vehicle via the RIS-assisted V2V broadcast link with no retransmissions. The communication performance is then evaluated using packet loss rate and object detection precision at various distances from the intersection, providing insight into the effectiveness of RIS in improving the reliability of CPM exchange in obstructed environments.

E. Scenarios and Validation

The performance of the RIS-enhanced V2X communication is tested under various conditions, including different speeds and varying positions of the moving car relative to the intersection. We evaluate the packet loss rate at various CPM transmission speeds, and CPM information freshness dynamics with and without RIS module. This allows us to assess the impact of vehicle speed, position, and distance on the reliability of the CPM exchange in both static and dynamic driving scenarios. Simulation results are validated against theoretical models and simulated empirical data, ensuring that the framework accurately represents the behavior of RIS-assisted communication. By comparing these performance metrics across different scenarios, we demonstrate the potential of RIS technology in enhancing CCAM systems.

III. Results and Discussions

In this section, we present the results of our simulation experiments, which evaluate the performance of RIS-assisted V2X communication in enhancing the reliability of CPM exchange. We analyze the impact of RIS on packet loss rate, under various transmission speeds. Additionally, we evaluate the performance of object detection on the static vehicle's field of view and the transmission of video streams with detection results as well as the raw frames to the moving vehicle. We compare real-time inference capabilities of YOLOv7 and quantify how frame compression balances packet losses with information freshness for safety-critical messages. Through communication-aware parameter optimization, we examine the trade-offs between confidence thresholds (0.1–0.9), non-maximum suppression (NMS) parameters, and their impact on end-to-end delay. The results demonstrate the effectiveness of RIS in mitigating communication disruptions caused by obstacles and improving the overall reliability of CPM exchange in cooperative driving environments.

TABLE II: Packet Loss Rate at Different Transmission Speeds

Transmission Speed (Mbps)	**Packet Loss Rate** (%)	
	Without RIS	**With RIS**
120	83.2	31.3
180	86.5	39.1
240	90.4	47.9
360	94.1	53.5
480	97.8	60.2
720	100	81.8
960	100	88.5
1080	100	96.3

A. Packet Loss Rate

Packet loss rate (PLR) measures the percentage of data packets that fail to reach the moving vehicle, directly impacting communication reliability [13]. We analyze the impact of varying transmission speeds and the presence of RIS on PLR. The results of these evaluations are summarized in Tab. II. It could be observed that PLR increases significantly with higher transmission speeds in the absence of RIS, rising from $83.2\,\%$ at $120\,\mathrm{Mbit/s}$ to $100\,\%$ at $720\,\mathrm{Mbit/s}$ and above. Higher speeds are more sensitive to noise, which increases the likelihood of packet errors. The introduction of RIS significantly reduces PLR across all transmission speeds. For example, at $120\,\mathrm{Mbit/s}$, PLR drops from $83.2\,\%$ without RIS to $31.3\,\%$ with RIS. This improvement stems from the RIS ability to optimize signal propagation by dynamically adjusting phase shifts of its reflecting elements, enhancing signal coherence at the receiver and mitigating multipath fading and interference.

B. Object Detection Performance

To further enhance situational awareness, we perform object detection on the moving vehicle's field of view using two variants of YOLOv7: the tiny model and the large model. The tiny model, with around 6.2M trainable parameters, is optimized for real-time performance, achieving frames per second (FPS), while the large model, with around 36.9M trainable parameters [12], provides a higher mean average precision (mAP), i.e., a metric that evaluates detection accuracy by considering both precision and recall across all classes [14] for improved detection precision. The detection results are validated against ground truth data to ensure the reliability of the object detection process. Tab. III summarizes the performance of YOLOv7 for various input resolutions and model variants. The results demonstrate that the tiny model achieves higher FPS, making it suitable for real-time applications with lower computational resources. However, the large model provides higher mAP, ensuring better detection

TABLE III: Performance of YOLOv7 for Object Detection

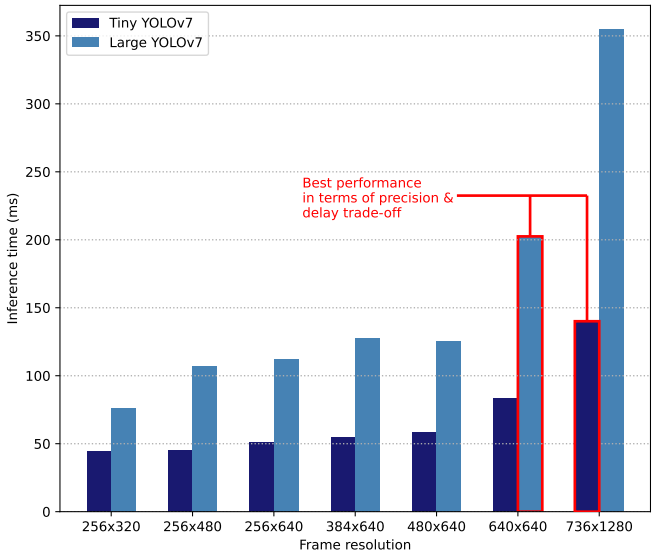
Model Variant	Input Resolution	FPS	mAP (%)
Tiny	256 × 320	286	38.7
	256 × 480	161	51.4
	256 × 640	157	52.9
	384 × 640	143	54.6
	480 × 640	114	55.9
	640 × 640	97	69.7
	736 × 1280	84	84.6
Large	256 × 320	154	43.7
	256 × 480	114	53.1
	256 × 640	99	56.7
	384 × 640	71	67.5
	480 × 640	56	69.1
	640 × 640	45	71.2
	736 × 1280	36	85.4

accuracy at the cost of reduced FPS. Based on the specific requirements of the simulation, such as real-time processing or high detection precision, an appropriate model variant and input resolution can be selected.

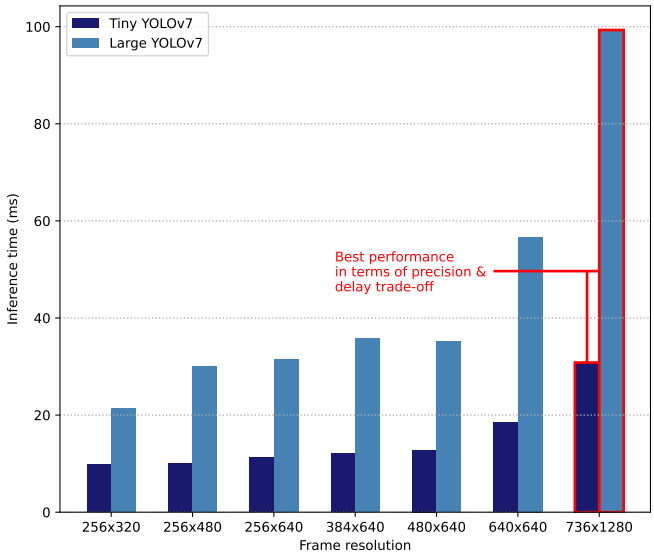
1) Real-Time Inference Comparison: To evaluate the real-time inference capabilities of YOLOv7, we conducted experiments on two compute engines: a) NVIDIA GeForce GTX 960 (1024 CUDA cores, 4GB GDDR5, Core Clock @1.17 GHz; and b) NVIDIA GeForce GTX 1660 Ti (1408 CUDA cores, 6GB GDDR6, Core Clock @1.77 GHz). Fig. 4 presents the inference time versus model size for both compute engines. The results demonstrate that the GTX 1660 Ti achieves significantly lower inference times compared to the GTX 960, owing to its higher number of CUDA cores and faster memory bandwidth. For example, the large model at an input resolution of 640×640 achieves an inference time of $55.8\,\mathrm{ms}$ on the GTX 1660 Ti, compared to $207.3\,\mathrm{ms}$ on the GTX 960.

The inference time of the object detection model directly impacts the timeliness of the CPM exchange between the moving and static vehicles. Lower inference times enable faster processing of the video stream coming from the camera sensor of the moving vehicle, ensuring that the detected objects and their metadata are transmitted to the static vehicle with minimal delay. This is critical for real-time decision making in autonomous driving scenarios, where even small delays can compromise safety and efficiency. The integration of RIS-assisted communication further mitigates the impact of inference delays by optimizing the transmission of CPMs. RIS dynamically adjusts the propagation environment, ensuring that the object detection results are transmitted to the static vehicle with minimal latency, even in obstructed environments.

2) Impact of Frame Compression on Packet Loss and Information Freshness: In this section, we examine the cooperative perception quality versus latency trade-off in the presence of RIS, something that to the best of our knowledge has not been investigated in literature as of now. Our evaluation demonstrates how using RIS reduces information aging



(a) Using NVIDIA GeForce GTX 960.



(b) Using NVIDIA GeForce GTX 1660 Ti.

Fig. 4: Inference time vs. model size for YOLOv7 Tiny and Large models across different CARLA frame resolutions.

through packet loss mitigation, with AoI serving as the critical metric that quantifies the time sensitivity of cooperative perception data in autonomous vehicle networks. The size of the communicated data and thus the communication latency can be reduced by leveraging appropriate compression mechanisms. However, compression comes at the cost of reduced object detection precision, highlighting the fundamental trade-off we investigate. This trade-off is affected by the content of each CPM message. While in cases where a frame may be transmitted over multiple CPMs (where packet losses would negatively impact object detection precision), our current simulator cannot support this option. Therefore, in this work

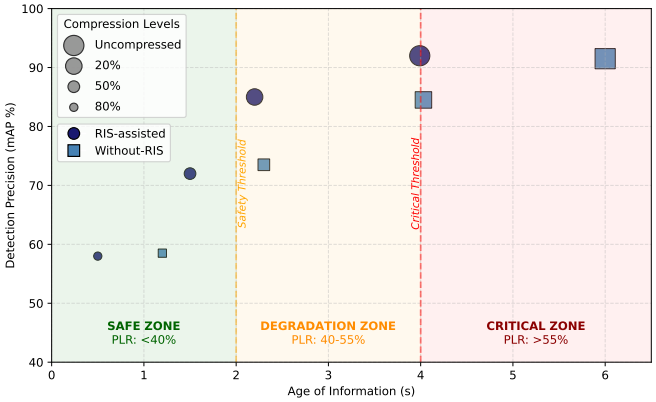


Fig. 5: Trade-off between CPM information freshness and detection precision at different frame compression levels.

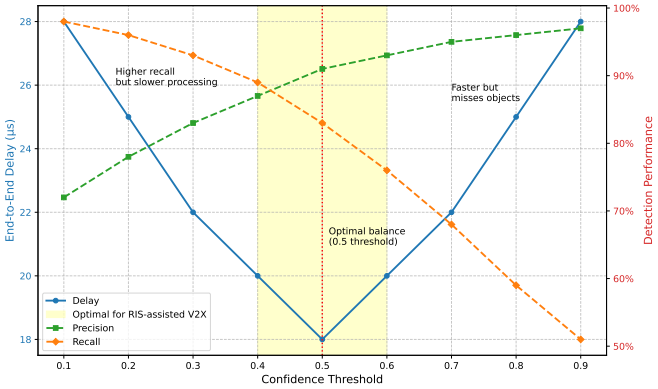


Fig. 6: Trade-off between CPM end-to-end delay and detection precision at varying confidence thresholds.

we investigate the case where each frame is communicated over a single CPM, meaning packet losses primarily impact information freshness rather than immediate detection precision. The perception precision vs. AoI tradeoff for different compression levels is investigated and quantified using the developed simulation tool, demonstrating the beneficial effect of RIS deployment and guidelines as to the most suitable compression level.

Our experimental evaluation using YOLOv7 on GTX 1660 Ti GPU with 736×1280 resolution input frames reveals a critical three-way relationship between frame compression, transmission reliability, and information freshness. Fig. 5 demonstrates the trade-off between CPM information aging in the presence of packet losses and mAP for uncompressed frames, as well as those compressed at levels of $20\,\%$, $50\,\%$, and $80\,\%$ transmitted at $720\,\mathrm{Mbit/s}$. The results show that higher compression reduces transmission latency (crucial for timely CPM exchange) but degrades localized detection accuracy due to loss of fine-grained spatial features. At $50\,\%$ compression, the system achieves an optimal balance, reducing delay by $12\,\%$ while maintaining $92\,\%$ of the baseline mAP observed with uncompressed frames. This compression-precision tradeoff directly impacts the AoI. Our empirical analysis establishes a direct correlation between PLR and information staleness, with particularly severe consequences when AoI exceeds the $2\,\mathrm{s}$ safety threshold (τ_s). The system exhibits a non-linear degradation pattern where:

$$\begin{aligned} \mathrm{AoI} &= (1 - \mathrm{PLR})t_0 + \mathrm{PLR}(t_0 + \Delta t) \\ &= t_0 + \mathrm{PLR}\Delta t \end{aligned} \tag{1}$$

where t_o is the baseline transmission latency, and Δt represents time window between two updates. We observe three distinct operational regimes: below $40\,\%$ PLR, the system maintains acceptable freshness with mean AoI under $2\,\mathrm{s}$; between $40\,\%$ to $55\,\%$ loss, we see accelerated degradation where nearly a quarter of messages exceed the safety threshold; and beyond $55\,\%$ loss, the system enters a critical regime with over $60\,\%$ of object detections becoming stale. This degradation follows an exponential decay pattern, indicating rapid deterioration of information utility. The introduction of RIS technology proves particularly effective in the $40\,\%$ to $55\,\%$ loss range, reducing AoI threshold violations by $68\,\%$ through intelligent phase-shift optimization of the reflected signals. The quantitative relationships derived from this analysis provide fundamental guidelines for system parameter selection and RIS configuration in real-world deployments.

3) Communication-Aware YOLO Parameter Optimization: YOLO's performance is highly sensitive to parameter selection, particularly the confidence threshold [15], which directly affects both detection reliability and communication efficiency. Since cooperative perception systems depend on timely and accurate information exchange, these parameters must be optimized considering the underlying communication conditions. We analyze the impact of YOLOv7 tiny model's confidence threshold and NMS parameters on both detection precision and end-to-end delay for CPM exchange. The confidence threshold is a critical parameter that dictates the minimum detection score required for an object to be considered valid. This score reflects the model's certainty that a detected bounding box contains an object of the predicted class. A high threshold (e.g., 0.8) ensures reliable detections but risks missing low-confidence true positives, while a low threshold (e.g., 0.2) increases recall at the cost of false positives and higher bandwidth usage [16]. Similarly, NMS, controlled by the intersection-over-union (IoU) threshold, determines how overlapping detections are merged. A high IoU (e.g., 0.7) preserves more detections, aiding recall but increasing communication load, whereas a low IoU (e.g., 0.3) reduces redundancy at the risk of over-suppressing valid detections [17]. Together, these parameters shape the trade-off between detection accuracy and communication efficiency, necessitating joint optimization for CPM performance.

Fig. 6 demonstrates this relationship through three key metrics: end-to-end delay, detection detection precision, and recall rate. The results show a U-shaped latency profile, with optimal end-to-end delays of $18\,\mu\mathrm{s}$ occurring at mid-range confidence thresholds (0.4–0.6). This region (highlighted in

yellow) represents the operational sweet spot for RIS-assisted V2X networks, where delay increases by only $22\,\%$ from the minimum while maintaining more than $83\,\%$ recall and more than $87\,\%$ precision. Beyond this range, system behavior diverges sharply: lower thresholds (0.1–0.3) improve recall to $98\,\%$ but incur $55\,\%$ higher latency, while higher thresholds (0.7–0.9) reduce delay by $35\,\%$ but compromise safety with recall dropping to $51\,\%$. The precision-recall gap narrows from 26 percentage points at threshold=0.1 to just 2 points at threshold=0.9, revealing an inherent accuracy-latency coupling. Our recommended operating point (threshold=0.5, marked by red dotted line) achieves $91\,\%$ precision with $83\,\%$ recall while keeping delays below $20\,\mu s$, satisfying the $100\,\mu s$ latency requirement for time-critical V2X applications. The stable plateau around this optimum (± 0.1 threshold variation) provides operational flexibility, with less than $5\,\%$ performance degradation across all metrics. These findings demonstrate that careful parameter tuning of the YOLOv7 can achieve an optimal balance between detection performance and communication efficiency for V2V applications.

IV. Conclusion

We investigated the potential of RIS to enhance the reliability of CPM exchange in CCAM systems. Through a comprehensive simulation framework integrating the CoopeRIS platform with CARLA and SUMO, we evaluated the impact of RIS on packet loss rate at various CPM transmission speeds, its impact on age of information, and object detection performance. We demonstrate three key advancements: (1) RIS reduces packet loss rates by up to $68\,\%$ across CPM transmission speeds, (2) maintains AoI below the critical $2\,s$ safety threshold even at PLRs of $40\,\%$ to $55\,\%$, and (3) optimizes object detection performance through communication-aware YOLO parameter tuning. Our results affirm that RIS significantly improves the performance of V2V communication, particularly in environments with obstacles or over longer distances. The simulation results revealed that RIS-assisted communication consistently outperforms traditional communication methods. Specifically, RIS mitigates packet collisions and signal degradation, even at higher transmission speeds and longer distances. The integration of RIS into CCAM systems offers a promising solution to enhance the reliability of collective perception services, enabling safer and more efficient autonomous driving. By dynamically adjusting signal propagation paths, RIS ensures robust communication even in obstructed environments, paving the way for the widespread adoption of CCAM technologies. Future work will focus on further optimizing RIS configurations, exploring their impact in dynamic and complex driving scenarios, and addressing additional challenges such as latency reduction and scalability. Finally, the simulation framework will be released to the community as open source software.

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