Edge-Assisted Collaborative Perception in Autonomous Driving: A Reflection on Communication Design

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ABSTRACT

Collaborative perception enables autonomous driving vehicles to share sensing or perception data via broadcast-based vehicle-to-everything (V2X) communication technologies such as Cellular-V2X (C-V2X), hoping to enable accurate perception in face of inaccurate perception results by each individual vehicle. Nevertheless, the V2X communication channel remains a significant bottleneck to the performance and usefulness of collaborative perception due to limited bandwidth and ad hoc communication scheduling. In this paper, we explore challenges and design choices for V2X-based collaborative perception, and propose an architecture that leverages the power of edge computing such as road-side units for central communication scheduling. Using NS-3 simulations, we show the performance gap between distributed and centralized C-V2X scheduling in terms of achievable throughput and communication efficiency, and explore scenarios where edge assistance is beneficial or even necessary for collaborative perception.

CCS CONCEPTS

• **Networks** → **Network protocol design**; **Link-layer protocols**; **Network simulations**.

KEYWORDS

Autonomous Driving, Collaborative Perception, Edge Computing, Cellular-V2X, Sensing-based SPS, NS-3

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1 INTRODUCTION

Autonomous driving vehicles (ADVs) are expected to be central to intelligent transportation systems (ITSs) and smart cities. ADVs utilize on-board sensors such as cameras and LiDARs to sense and perceive the surrounding environment, and make real-time safety-critical driving decisions without or with minimal human intervention. Recent advances in ADVs promise to eliminate accidents, reduce emission, and enhance transportation efficiency [21]. Wide deployment of ADVs expects to achieve over $800 billion annual social benefits by 2025 due to improved road safety, reduced congestion and decreased energy consumption [21].

While promising, the current ADV design is limited by inaccuracy of sensors and real-time inference models, insufficient computation power, and incomplete information on road conditions due to limited sensing range and blockage. *Collaborative perception*, as a method of data sharing and fusion between ADVs, is a promising technology and a major recent research thrust for addressing these issues [13]. In collaborative perception, vehicles broadcast sensing and perception data via vehicle-to-everything (V2X) communications, and each vehicle fuses received data with its own perception data to improve accuracy and remove blind spots. Recent studies show that collaborative perception can complement on-board sensors and extend the awareness range of vehicles [19], especially in complex road conditions where blockage of view is common [12].

Despite its benefits, collaborative perception can drastically increase communication load and overhead in V2X communications, and is subject to the channel capacity of the V2X technology applied. Insufficient communication resources not only degrade collaborative perception performance in terms of accuracy and latency, but also affect other vehicular applications such as collaborative maneuvering, route planning and entertainment. This is especially true in congested urban scenarios where many vehicles may compete to communicate in an ad hoc manner, leading to severe interference that further degrades the resources for effective transmissions.

This paper studies the communication issues for collaborative perception. Focusing on Cellular-V2X (C-V2X) standardized by 3GPP [1], we develop NS-3 simulations to show the performance of centralized versus ad hoc C-V2X communications for collaborative perception. Further, we investigate edge-assisted C-V2X broadcast scheduling as an alternative to the default C-V2X ad hoc mode, and show that in urban scenarios with heavy load, edge-assisted scheduling can achieve over 60% effective throughput improvement, while significantly reducing the amount of ineffective transmissions due to collision and packet losses. Based on the simulations, we discuss design challenges of V2X-based collaborative perception, and suggest directions where further investigation is needed for enabling practical collaborative perception in autonomous driving.

2 BACKGROUND FOR V2X-BASED COLLABORATIVE PERCEPTION

2.1 Collaborative Perception

Collaborative perception refers to the ability for vehicles to exchange their sensing and perception data, and merge the local

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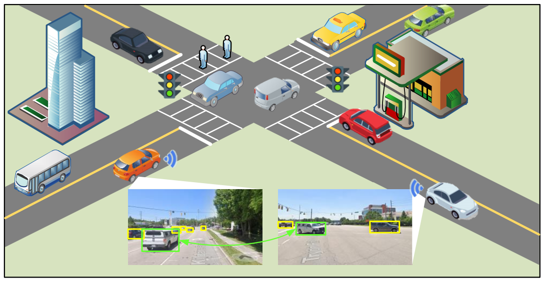


Figure 1: Collaborative perception example: two vehicles share sensory data to remove blind spots of each other, based on commonly visible (co-visible) objects in their views [12].

view of each vehicle with the received views of other vehicles for more accurate perception and better decision making, as shown in Fig. 1. It enables shared awareness of the surrounding environment by extending each vehicle's perception ranges, compensating for sensor/perception deficits, and removing blind spots. Tasks that can be performed via collaborative perception include object detection [12], lane detection [11], localization [17], real-time mapping [14], etc. In many existing methods, raw sensory data obtained from on-board sensors of a vehicle (*e.g.*, camera and LiDAR images) are directly shared to near-by vehicles via V2X broadcast communications, along with the sending vehicle's metadata such as location, velocity and orientation. Each receiving vehicle then merges the received data with its own data via an on-board data fusion unit, to derive the merged view including the objects, their relative locations, and mapping to 3D physical space. To ensure accurate mapping from the received view to the local view, processes such as correspondence identification [12] are employed at each vehicle.

Unlike raw data sharing, recent studies show that sharing only *representations* of raw data can reduce communication overhead and improve latency performance [12]. For instance, by only sharing perceived features (*e.g.*, color, shape and size) and/or 3D locations of objects, collaborative 3D localization can be achieved with high accuracy but magnitudes of reduction in communication overhead [12]. Moreover, unlike raw data which cannot be sliced and partially utilized, representation data such as object features can be selectively transmitted and utilized to further reduce communication load. For instance, in uncertainty-aware localization, only features that contribute to object location inference are needed, and features of objects with high uncertainties among vehicles can be prioritized for transmission to improve real-time localization accuracy. These properties lend much flexibility to perception-communication co-design, enabling highly efficient communication scheduling for the optimal real-time collaborative perception performance. One caveat for representation sharing is that each representation may be designed for a specific task (*e.g.*, localization, mapping, etc.), and hence more than one type of representation may need to be sent in each round to carry out all needed tasks.

2.2 V2X Communications

Communication design is foundational to the performance of collaborative perception. Recent development in V2X technologies have started providing support to collaborative perception use cases. The European Telecommunications Standards Institute (ETSI) and the Society of Automotive Engineers (SAE) have both recently launched standardization efforts for collaborative perception services [9, 18]. For instance, the ETSI ITS technical committee has finalized a Technical Report for Collective Perception Service (CPS) [9], which includes the definition of higher-layer Collective Perception Message (CPM) formats to be used in the ETSI ITS-G5 communication technology [7]. ITS-G5 is a European Standard for V2X communications based on IEEE 802.11p Wireless Access in Vehicular Environments (WAVE) and IEEE 1609; the US counterpart is Dedicated Short-Range Communication (DSRC) [20], a project led by the US Department of Transportation. Both use the same spectrum in the 5.9GHz band, which is the official ITS spectrum in most countries.

A new V2X standardization effort is Cellular-V2X (C-V2X) led by The 3rd Generation Partnership Project (3GPP) [1]. While ITS-G5 and DSRC are both based on IEEE 802.11 wireless local area network (WLAN) technology, C-V2X utilizes 3GPP 4G Long-Term Evolution (LTE) and 5G New Radio (NR) standards for V2X communications. It uses the same 5.9GHz band as ITS-G5 and DSRC. As of 2021, C-V2X is expected to replace (or co-exist with) ETSI ITS-G5 and DSRC, with the US Federal Communications Commission (FCC) reallocating the 5.9GHz band for DSRC to C-V2X in 2019 [10], and ETSI approving a new European Standard defining C-V2X as the access layer technology for ITS devices in 2020 [8]. Study has shown that C-V2X has superior throughput over IEEE 802.11p in realistic scenarios [16]. The benefit may specifically come from the access control algorithm employed in the C-V2X ad hoc mode (Mode 4 in LTE-V2X or Mode 2 in NR-V2X), *sensing-based semi-persistent scheduling (S-SPS)*, which outperforms Carrier Sensing Multiple Access (CSMA)-based algorithms employed in IEEE 802.11p [16].

2.3 Motivation of This Paper

Most existing V2X studies focus on the transmission of Collaborative Awareness Messages (CAMs), which are short messages exchanged by vehicles for mutual-awareness of each other's location in tasks such as collision warning or traffic estimation. The difference between CAMs and CPMs (Collaborative/Collective Perception Messages) is that CAMs contain only metadata about the vehicle itself (location, velocity, orientation, etc.), while CPMs contain sensory data or data representations obtained by the vehicle. Both CAMs and CPMs need to be transmitted and received periodically in real-time, but CPMs are commonly much larger than CAMs, posing a much larger load on the communication channel with the same or similar quality-of-service (QoS) requirements as CAMs including ultra-low latency. Hence serving CPMs is much more challenging than serving CAMs in V2X. Due to lack of related study, this paper performs a simulation study on C-V2X for collaborative perception, and discusses future directions implied by the result.

3 PRELIMINARY SIMULATION RESULTS

3.1 Sensing-based Semi-Persistent Scheduling

S-SPS is the access control algorithm used in the C-V2X ad hoc mode (LTE-V2X Mode 4 and NR-V2X Mode 2). Let V be a vehicle scheduling to transmit at time T. A resource is defined as a subframe (1ms) in the time domain, and a subchannel consisting of a certain number of Physical Resource Blocks (PRBs) in the frequency domain. Below we describe this algorithm in the high level, omitting protocol details and differences between LTE-V2X and NR-V2X:

(1) V defines a Selection Window of size W based on its latency requirement and traffic periodicity (*e.g.*, $W = 100$ms). It then identifies all resources within the Selection Window starting from T as candidate resources (CRs).
(2) V then defines a Sensing Window with size $W' = N \times W = 1000$ms, starting from time T–W' until T–1. V excludes all CRs that have been scheduled for transmission by other vehicles, or that have sensed average Reference Signal Received Power (RSRP) above a given threshold, in its Sensing Window. The average is taken over all N resources in the Sensing Window that has the same index as the CR in the Selection Window. If remaining CRs are below 20% of the total CRs in Step (1), this step is repeated with a 3dB-higher RSRP threshold.
(3) From the CRs remaining in Step (2), V picks the 20% CRs with the lowest average Received Signal Strength Indicator (RSSI). V randomly selects 1 CR to transmit its current packet. Also, V randomly generates a Reselection Counter (RS) R in a specific range based on W and its traffic periodicity, and reserves the picked CR for the next R Selection Windows.

After the resource is picked and reserved with the RS R, V can use the same resource for transmission in the next R windows, each deducting R by 1. The reservation is broadcast to all vehicles via Sidelink Control Information (SCI) messages sent along with each data packet. When R becomes 0, V can keep the current schedule with probability of P and a new RS R, or re-run the algorithm to reserve a new resource with $(1 - P)$ probability; by default $P = 0.8$.

This algorithm works well with short CAM messages, as 1 reservation is commonly sufficient for transmitting a periodic CAM of each vehicle [5]. Simulations have shown that C-V2X can support hundreds of vehicles for CAM transmission with negligible collision (<5%) [5]. For CPM, however, each vehicle may need to reserve many resources within one Selection Window to accommodate the large data size. Inevitably, this will increase collision, and lower the number of collaborative perception vehicles supported by C-V2X.

3.2 Scheduling Algorithm Implementation

To perform the simulation study, we extended an existing LTE-V2X Mode 4 simulator in NS-3 [5] to our target scenario. We modified the simulator to schedule for more than 1 packets in a Selection Window, based on the per-vehicle CPM data size. This enforces the real-time requirement for CPM that each message should be sent and received within a given deadline (*e.g.*, 100ms). Each packet is scheduled based on the S-SPS algorithm with no resource overlap with other packets of the vehicle. We assume each vehicle chooses a subchannel length that maximizes the bits-per-PRB that can be transmitted in one subframe according to [2], which in most cases corresponds to all available PRBs when the data size is large.

In addition to LTE-V2X Mode 4, we also implemented an *edge-assisted ideal scheduling* algorithm for comparison. The ideal algorithm assumes a centralized scheduler based on edge computing (*e.g.*, at a road-side unit or RSU), and schedules all vehicles within its range in a round-robin manner based on their data sizes. In case all vehicles' total CPM data size is more than that can be accommodated within one Selection Window, the scheduler will instruct all vehicles to reduce their data sizes to avoid collision while ensuring timely data sharing. Conceptually, this centralized scheduler can be viewed as a specific implementation of the in-coverage, centralized mode of C-V2X (LTE-V2X Mode 3 or NR-V2X Mode 1) for *broadcast-based collaborative perception*, since no scheduling algorithm for the centralized mode is defined in the 3GPP releases. The algorithm, however, can also be implemented at RSUs to focus on local management with dedicated power control, such as at a junction. We call this mode *Edge-Assisted Broadcast (EAB)* in the following.

Table 1: Default Simulation Parameters

Vehicle Parameters	
Number of vehicles (n)	5-20
Update interval (u) / Selection Window	100ms / 96ms
CPM data size	1, 207 to 48, 280 Bytes
Reselection probability (P)	0.8
Channel Parameters	
Channel bandwidth	10 MHz
PRBs per subchannel / # subchannel(s)	25 / 1
Maximum theoretical bitrate (b)	9.656 Mbps
Channel load factor (ϕ)	20% to 200%

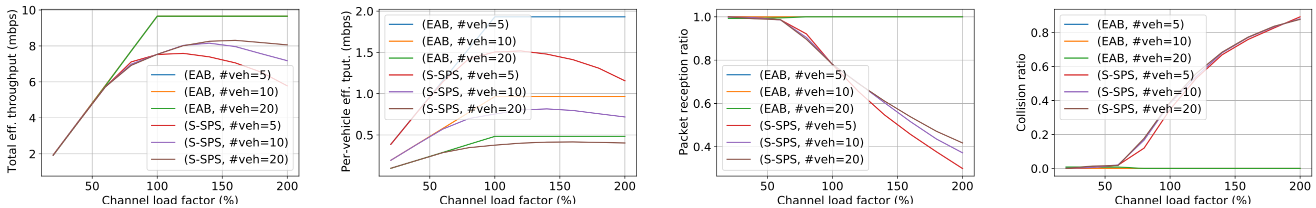
3.3 Simulation Settings

A 4-way junction is simulated with 2-way static traffic, simulating a scenario for collaborative blind spot removal as one of the most challenging scenarios in collaborative perception [12]. Table 1 shows simulation parameters used. Except those listed, other parameters are set based on [5]. CPM data size is based on channel load factor ϕ as a variable in the simulation, computed as $(\phi \cdot b \cdot (u/1000)/8)/n$ bytes (B), *i.e.*, it is equal to ϕ times how many bytes each vehicle could send within one update interval in the ideal schedule. Based on the default parameters and ϕ ranging from 20% to 200%, the CPM data size ranges from 1, 207 to 48, 280 bytes. We note that this is within the normal range of CPM data sizes based on state-of-the-art collaborative perception methods: from a most recent work [12], the data size ranges from 128B (a minimal representation) to 172KB (a full 180×320 raw RGB image). We show four metrics:

- *Total effective throughput (TET)*: total data successfully received by all vehicles, divided by the number of vehicles minus one as the number of intended receivers per message.
- *Per-vehicle effective throughput (VET)*: TET divided by the number of vehicles, as the average data volume that each receiver receives from each sending vehicle.
- *Packet reception ratio (PRR)*: fraction of broadcast packets successfully received by each receiver.
- *Collision ratio (CLR)*: ratio of packets transmitted with overlapping PRBs with other packets.

3.4 Simulation Results

Fig. 2 shows preliminary simulation results. In Fig. 2(a), S-SPS (LTE-V2X Mode 4) has comparable TET to EAB when channel load is low. When channel load is high ($\geq$ 60%), S-SPS shows degraded throughput due to resource competition. S-SPS could still improve its TET until the load becomes excessive (over 100% to 150%), at the cost of significantly degraded PRR and increased CLR in Figs. 2(c) and 2(d) respectively. This means that, to achieve a high throughput, vehicles must send more additional data, with a high risk of having a significant part of the sent data not received by most other vehicles, *i.e.*, transmission efficiency degrades. After a certain load threshold



(a) Total effective tput. (TET) **(b) Per-vehicle eff. tput. (VET)** **(c) Packet reception ratio (PRR)** **(d) Collision ratio (CLR)**

Figure 2: LTE-V2X Mode 3 (*Edge-Assisted Broadcast*, or *EAB*) versus Mode 4 (*Sensing-based Semi-Persistent Scheduling*, or *S-SPS*).

(*e.g.* 150% channel load), S-SPS further has degrading TET due to excessive ad hoc competition among vehicles. Meanwhile, EAB always achieves maximum efficiency regardless of load, and can fully utilize the channel when the load is high with close-to-one PRR and no collision. Regardless of load and scheduling algorithm, more vehicles broadcasting CPMs lead to lower per-vehicle throughput in Fig. 2(b). Thus when the spectrum is not enough for all vehicles to broadcast every piece of data, vehicle/data selection must be performed to ensure timely updates. In practice, at any time a mixture of centrally scheduled and ad hoc vehicles will be present, due to new vehicles arriving in the range of an edge node. Thus the perceived performance is likely to be a mixture of EAB and S-SPS shown in the figures. With the edge performing sensing-based scheduling, we expect that EAB can still greatly improve communication efficiency and PRR in the mixture case. Overall, the simulations show the inefficacy of ad hoc scheduling in congested urban scenarios, and justifies the necessity of edge-based scheduling for real-time, high-accuracy collaborative perception.

4 EDGE-ASSISTED COLLABORATIVE PERCEPTION: THE VISION

4.1 Communication-aware Design Challenges

Insufficient data rate: DSRC (IEEE 802.11p) provides a maximum data rate of 27Mbps [3], and LTE-V2X can support up to 100Mbps in high mobility scenarios [4]. While NR-V2X with millimeter-wave (mmWave) bands may achieve multi-Gbps data rates [4], no official mmWave bands have been licensed for V2X use. For raw data sharing, the data rate of a single vehicle may range from several to tens of Mbps depending on the sensor type (*e.g.*, camera versus LiDAR) and number. Thus even in moderately congested scenarios with tens of vehicles, the overall data rate would overwhelm the channel, and scheduling and data selection are needed.

Lack of global view and coordination: Ad hoc scheduling is a major bottleneck in V2X communications, leading to excessive collision and low effective throughput as shown in simulations. Especially in congested urban scenarios, the lack of global coordination and global view-based data selection can lead to highly ineffective collaborative perception. Edge computing could serve as such a "global" communication coordinator and view aggregator, with careful design of the communication and aggregation modules so as not to further increase overhead and decrease efficiency.

Data redundancy and uncertainty: When many vehicles are near-by, their views may significantly overlap, with redundant data about each object. In this case, not all vehicles' data are needed, and data deduplication is needed. On the other hand, each vehicle's

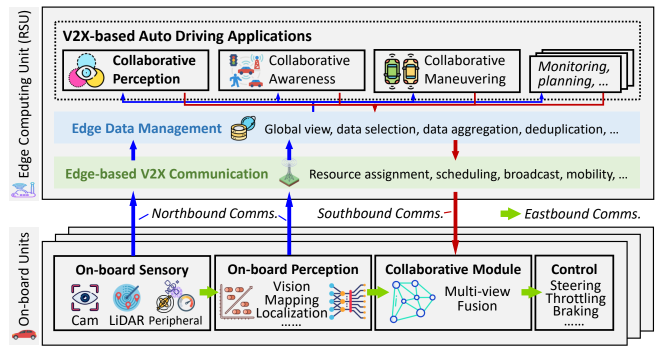


Figure 3: Edge-assisted collaborative autonomous driving.

data may have uncertainty regarding an object's type, shape and location [12], which calls for data selection before transmission to minimize uncertainty of vehicles' merged views.

Real-time constraints: In addition to the high data volume, collaborative perception use cases have stringent real-time requirements. Due to vehicle mobility and dynamic environmental changes, data must be delivered within a time limit (*e.g.*, 100ms-1s [9]) to be useful to vehicles. Also, the fresher a piece of delivered data, the more promptly can tasks be performed, which could improve safety and comfort of autonomous driving. Thus age-of-information (AoI) could play a key role in optimal communication design.

4.2 Edge-Assisted Collaborative Perception

Based on the challenges, we advocate that edge assistance is critical to collaborative perception and other ADV applications in real world. A reference architecture is shown in Fig. 3. Two major components of the system are the on-board units including sensory, perception, collaborative module, and control, and the edge computing unit residing on RSUs; the two components are aware of each other and communicate over north/southbound V2X interfaces. In the edge unit, two control plane layers provide basic functions shared by different applications. The Edge Data Management module collects CPMs (and other data) and builds a global view, with which data selection, aggregation and deduplication are performed based on application needs. The Edge-based V2X Communication module manages broadcast communications for edge- and vehicle-initiated traffic. Various collaborative applications can be built atop these two common layers utilizing the provided functions.

4.3 Research Directions

Based on the proposed architecture, we next highlight directions where research and development is crucially needed to enable high-performance real-time edge-assisted collaborative perception.

Direction 1: edge-based communication design. To address inadequate communication resources and collision, centralized coordination should be conducted by the edge node. Novel resource management and scheduling are needed to tackle unique challenges in collaborative perception, including throughput and real-time requirements, and meanwhile potentially high data redundancy. AoI-based metrics are important for satisfying the real-time requirement. However, existing AoI metrics are application-agnostic and do not consider characteristics of collaborative perception such as data redundancy and uncertainty across sources, and diverse AoI requirements for different objects such as low-mobility pedestrian versus high-mobility vehicles. Application-aware metrics are needed for optimal communication design supporting safety-critical collaborative perception (and other) applications.

Direction 2: edge-assisted communication-efficient collaborative perception. Application design is also important for efficient and effective collaborative perception. Specifically, application design should be aware of the limited communication resources, and should be closely coupled with communication design to provide efficient transfer of the most critical data for collaborative perception. For instance, when the data volume for collaborative perception exceeds the channel capacity, vehicles should collectively select the most important data to transmit, such as data on the most uncertain objects or areas, or outdated data that require refreshing. This is best achieved when an edge node can centrally coordinate data selection and transmission among local vehicles. Further, the edge node may maintain an aggregated view based on received data, and also participate in collaborative perception with its own sensors such as traffic cameras. The design space of joint edge-vehicle collaboration is huge and requires extensive research.

Direction 3: interplay between collaborative perception and other applications. In practice, collaborative perception coexists with other autonomous driving and ITS functions, including but not limited to: collaborative awareness [6], collaborative maneuvering [15], traffic monitoring/planning, etc. Different applications have different requirements and criticality levels. These applications may interact in the data, computing and communication domains. For instance, collaborative perception may use the same sensory data as collaborative awareness and traffic monitoring,and all these services use the same on-board/edge computing resources and communication channel. Application-aware, cross-layer management of data, computing and communication for ITS applications is an important direction that requires synthesis of multiple related areas including but not limited to distributed edge computing, communication design, network slicing, and performance modeling.

5 CONCLUSIONS

This paper aimed to provide a preliminary study of edge-assisted collaborative perception in autonomous driving from a V2X communication design perspective. Collaborative perception and V2X communications were traditionally studied in two separate subareas, and little research has been done on the practical performance of collaborative perception with current V2X communication protocols. We showed via preliminary simulations that collaborative perception with ad hoc V2X broadcast could result in low channel efficiency, high congestion and low packet reception ratio. Edge-assisted communication coordination was proposed as a solution to the inefficiency problem. Still, lack of sufficient communication resource was identified as a major bottleneck for collaborative perception applications even with edge coordination, and several challenges exist for implementing real-time, high-accuracy collaborative perception in real-world scenarios. We finally concluded this paper with several future directions along which research and development must be conducted to realize practical V2X-based collaborative perception in autonomous driving.

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