Relevance-Aware Semantic Communication for Intelligent Collective Perception System

Romain Tessier [1,2], Oyunchimeg Shagdar [2], Bruno Monsuez [1]

[1] *U2IS, ENSTA, Institut Polytechnique de Paris*, 828 Bd. des Maréchaux, Palaiseau, France
[2] *Ampere Software Technology*, 1 Av. du Golf, Guyancourt, France
Email: {romain.tessier, bruno.monsuez}@ensta.fr, oyunchimeg.shagdar@ampere.cars

***Abstract*—Autonomous vehicles face critical limitations when navigating dynamic environments where occlusions or sensor range constraints prevent full situational awareness. Cooperative Intelligent Transport Systems (C-ITS) offer a solution by enabling vehicles to share perception data. However, the uncontrolled volume of exchanged messages leads to congestion and interpretation challenges. This paper proposes a context-aware approach to collaborative perception that transmits only semantically relevant information. By leveraging ontologies to build a knowledge graph of the driving scene, vehicles can reason over their environment, identify safety-critical events, and generate Semantic Collective Perception Messages (S-CPMs). These messages encode not just raw data, but meaningful, situationally prioritized insights, improving decision-making and communication efficiency. A hidden pedestrian use case demonstrates the framework's ability to anticipate and communicate high-risk interactions even in the absence of direct visibility. This semantic approach lays the groundwork for intelligent V2X systems that communicate with precision, relevance, and safety in mind.**

***Keywords*-Collaborative Perception; V2X; Ontology; Context-aware; Semantic-Communication.**

I. INTRODUCTION

This work advances our prior research on semantic and context-aware collaborative perception by integrating dynamic relevance estimation mechanisms and a refined ontology-based message generation process [1].

As the global number of vehicles on the road continues to rise, ensuring road safety remains a critical concern. According to the World Health Organization [2], approximately 1.2 million people died in 2023 due to road traffic crashes, with countless more suffering non-fatal injuries. In response to these alarming statistics, the automotive industry faces mounting pressure to improve vehicle safety systems aimed at preventing accidents and reducing fatalities. Automated driving technologies play a key role in this effort by enabling real-time perception, analysis, and response to complex driving environments. Despite these advancements, automated vehicles still face limitations when making decisions based on their own perception of the environment, particularly in scenarios where obstacles obstruct a vehicle's line of sight or where objects are out of sensor range [3][4]. To address these limitations, C-ITS have emerged as a promising solution [5]. By facilitating real-time information exchange among vehicles, infrastructure, and other road users, C-ITS enhances situational awareness beyond the capabilities of onboard sensors alone. Leveraging Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication, C-ITS enables vehicles to access a broader array of information from nearby vehicles or RoadSide Units (RSUs), allowing them to make more informed decisions in critical situations. By sharing data on traffic conditions, potential hazards, and road infrastructure, C-ITS offers a proactive approach to accident prevention that goes beyond the limitations of non connected autonomous systems.

Integrating Collective Perception Services (CPS) within the C-ITS framework represents a crucial step toward achieving safer and more efficient roadways [6][7]. CPS allows vehicles to collaboratively perceive and interpret road users, significantly improving their global perception. The Collective Perception Message (CPM) is the standardized message format used to transmit aggregated data which contain information relative to the locally-detected elements. Particularly valuable is the ability to share data about occluded or out of sensor range objects in real time, which enhances a vehicle's capacity to anticipate and respond to hidden dangers. However, as the number of connected nodes—such as vehicles and infrastructure—continues to grow, so does the volume of data transmitted over communication channels. Given that each CPM usually includes data on the perceived elements, this exponential increase in data can lead to communication congestion, resulting in latency, energy over-consumption, and complexities in merging data across heterogeneous sources.

In the context of vehicular networks, effective communication relies not only on the volume of transmitted data but also on its contextual relevance to the receiver. As conceptualized by Shannon's Information Theory, information corresponds to the reduction of uncertainty, or entropy [8][9]. Accordingly, relevant information is that which significantly decreases the receiver's uncertainty about the driving environment. In collaborative perception, this means that transmitted data should be selected based on its potential to support timely and accurate decisions by downstream systems. However, the relevance of a given piece of information is not absolute—it depends on the receiver's context and decision-making process. For example, an Automatic Emergency Braking (AEB) system requires highly precise, short-range predictions to initiate immediate safety actions, whereas an Autonomous Driving (AD) module benefits from broader, long-term situational awareness, such as anticipating pedestrian intent. In both cases, not all sensed or shared data contributes equally to system performance. To address this, we adopt an ontology-based approach that enables vehicles to formally represent and reason over their observed environment. This structured representation supports the identification of safety-critical situations and the prioritization of messages accordingly. By doing so, the system can dynamically adapt the frequency and content of CPMs, ensuring that only semantically relevant and high-impact information is communicated.

This paper is organized as follows. Section II reviews the current state of the art in congestion control and semantic communication for vehicular networks. Section III introduces a formal problem formulation that defines the collaborative perception setting, including the structure of observations, transmissions, and information relevance. Section IV presents the ontological framework used to represent and reason about the driving scene. Section V describes how contextual relevance is estimated through semantic reasoning over a knowledge graph. Section VI details the construction and transmission of semantically enriched CPMs within the C-ITS communication stack. Section VII discusses the limitations and implementation challenges of the proposed framework, including issues related to ontology standardization, real-time reasoning, and integration into ADAS pipelines. Finally, Section VIII concludes the paper and outlines potential directions for future work.

II. Related Work

Mitigating channel congestion has been the main concern in a large number of research activities. For example, in [10], vehicles reduce the CPM generation frequency in high-density areas. Decentralized Congestion Control (DCC) techniques have been proposed to allow individual nodes to autonomously adjust their transmission rates based on channel congestion level observed locally [11–14]. While these congestion control systems effectively alleviate network congestion, they often lack explicit consideration of context. In critical scenarios, this can lead to potentially harmful information gaps. To address this, some solutions incorporate context-awareness. For example, [15] proposes limiting collaborative communication to the most relevant nodes by creating a matching score between nodes. However, in C-ITS, where actors change rapidly, this approach is incompatible with the handshake mechanism explained in Who2Com [15]. Consequently, other studies propose limiting communication within geographical zones to ensure a level of relevance. In Direct-CP [16], collaborative communication is monitored by infrastructure based on each vehicle's maneuver intent. In contrast, Where2Com [17] does not rely on infrastructure to manage communication; instead, it uses a spatial confidence map at each agent to facilitate pragmatic compression, guiding agents on what to communicate, with whom, and whose information to aggregate. Additionally, [18] introduces a protocol that takes context into account for CPM generation frequency by aggregating information about the communication channel and environmental context (e.g., other vehicles and road layout). However, these solutions do not ensure that transmitted messages remain semantically relevant to the receiver; in other words, they do not consider what information will be efficiently consumed. Consequently, the receiver must infer semantic information about the sender's context, which may lead to interpretation issues.

To tackle these challenges, recent studies advocate for semantic communication between vehicles, which aims to convey meaningful content with inherent contextual value. For instance in [19], the authors implemented collaborative perception by extracting semantic features that are gathered and computed by an edge server. This concept of communicating high semantic-value information is also explored in [20–23] where a semantic encoder/decoder achieves higher transmission efficiency. This approach is demonstrated in [24] for image segmentation: rather than sending a full image (6 MB), it can be advantageous to transmit only the semantic interpretation of the image (30.5 KB). However, in semantic communication, the data is not merely compressed; it is reduced to the essential meaning. Thus, both the sender and receiver must have some form of shared knowledge to encode and decode the information effectively. This notion of a knowledge base can be linked to situational context, as the context forms part of the vehicle's knowledge. Finally, [25] provides initial steps for implementing semantic communication in V2X, introducing a new layer between the application layer and the transport/network layer. The authors illustrate the benefits of semantic communication through use cases such as adaptive traffic light management and collaborative driving. In this work, we aim to advance these efforts by (i) enhancing context-awareness in collaborative perception to generate situationally relevant messages, and (ii) adding semantic precision to collaborative messages, thereby minimizing interpretation issues and improving decision-making capabilities.

III. Problem Formulation

In a collaborative perception setting, vehicles both *observe* and *receive* overlapping targets information, fusing local sensor readings with messages from peers to enhance situational awareness. The system under study comprises $\mathcal{M} = \{1, \dots, M\}$ road users, of which $N \leq M$ are connected vehicles, forming the set $\mathcal{C} = \{1, \dots, N\}$. Each connected vehicle $i \in \mathcal{C}$ observes each target k (from the set $\mathcal{M}$) through a state vector

$$\hat{\mathbf{x}}_{i,k}(t) = \begin{bmatrix} p_k(t) \\ v_k(t) \\ \theta_k(t) \\ a_k(t) \end{bmatrix},$$

where p, v, θ and a denote position, velocity, heading and acceleration, respectively. Visibility is captured by

$$b_{i,k}(t) = \begin{cases} 1, & \text{if } i \text{ senses target } k \text{ at } t, \\ 0, & \text{otherwise,} \end{cases}$$

and each potential transmission from i to j about k is governed by

$$u_{i \to j,k}(t) \in \{0, 1\},$$

We define the *information set* available to vehicle $j \in \mathcal{C}$ about target $k \in \mathcal{M}$ at time t as the union of its own local observation and all received messages from peers. Formally:

$$\mathcal{I}_{j,k}(t) = \underbrace{\{\, b_{j,k}(t)\, \hat{\mathbf{x}}_{j,k}(t) \,\}}_{\substack{\text{own observation} \\ \text{(if visible)}}} \cup \underbrace{\bigcup_{i=1}^{N} \{\, b_{i,k}(t-\tau)\, \hat{\mathbf{x}}_{i,k}(t-\tau) \mid u_{i\to j,k}(t-\tau) = 1 \,\}}_{\text{received observations}}. \quad (1)$$

Here:

- $b_{i,k}(t) \in \{0,1\}$ is the visibility indicator of target k to vehicle i.
- $\hat{\mathbf{x}}_{i,k}(t)$ is the state vector $[p_k, v_k, \theta_k, a_k]$ observed by i at time t.
- $u_{i\to j,k}(t) \in \{0,1\}$ indicates whether i transmits its observation of k to j at time t.
- τ is the delay between the generation of the data by the observer i and its usage by the receiver j at time t.

This precisely captures, for each j, k, the mixture of locally generated and peer-received information available at any given instant.

This formulation assumes that the core objective of CPS is to provide each connected vehicle with timely and accurate information about all other road users. Under this assumption, the goal is to reduce the ego vehicle's perception uncertainty regarding its surrounding environment, thereby enabling more informed and safer decision-making. Redundant or imprecise transmissions are undesirable, as they consume communication resources without meaningfully enhancing the receiver's awareness. To address this, each transmitter $i \in \mathcal{C}$ optimizes its message generation decision $u_{i\to j,k}(t)$ with respect to a shared communication objective. Rather than broadcasting frequently and independently, transmitters coordinate their transmissions in a distributed and complementary manner to ensure that all targets $k \in \mathcal{M}$ are covered. This strategy promotes an even distribution of the transmission load, with connected vehicles collectively sharing the responsibility of informing their peers. As a result, each receiver $j \in \mathcal{C}$ can maintain a high-frequency, low-uncertainty perception of surrounding targets using only a limited number of CPMs. This maximizes perception accuracy while minimizing communication overhead.

However, not all information has the same value. The impact of shared data varies depending on the external situation and the internal context of the decision-making process that consumes it. In hierarchical decision-making architectures, the relevance of information is evaluated differently at each layer, ranging from high-level route planning to low-level motion control [26–28].

The internal context of the receiving vehicle, such as its current goal, position, maneuver stage, or driving intent, directly influences which pieces of information are considered useful. For example, at an unsignalized intersection, a vehicle approaching the crossing must closely monitor lateral traffic with unclear right-of-way. In such a case, timely and accurate information about cross-traffic is critical, while data about distant vehicles or non-threatening agents may be irrelevant [29]. Consequently, not all shared information contributes equally to decision quality. Transmitting irrelevant or low-impact data not only wastes bandwidth but may also introduce unnecessary computational load. An effective communication strategy must therefore go beyond reducing global uncertainty. It must be context-aware and prioritize the transmission of semantically relevant data tailored to the receiver's situational needs. In practice, this means that the set of useful information is often a small subset of all accessible data. This distinction becomes especially important in safety-critical tasks such as collision avoidance, which demand high levels of precision and low latency. In a collaborative perception framework, the reacting agent is not the observer, but the receiver, whose decisions are subject to communication and processing delays. This delay-sensitive structure amplifies the need to transmit only relevant and actionable information. Sharing data that does not contribute to the receiver's immediate awareness not only wastes resources but may also lead to late or suboptimal decisions. Therefore, early recognition of potentially dangerous situations, before they escalate, is essential. Prioritizing contextually relevant information allows the system to allocate communication resources more effectively, sustaining high safety standards despite delay constraints.

Nevertheless, estimating the potential value of information for other vehicles is inherently challenging. Transmitters typically lack full knowledge of the receiver's internal state, including its goals, plans, or decision criteria. Instead, they must infer relevance from observable contextual cues. The challenge, then, is to design communication policies that prioritize information likely to be beneficial, while filtering out data known to be irrelevant.

One promising direction is to ground communication decisions in established accidentology research, which identifies scenarios where information sharing has demonstrable safety benefits. For instance, the European SECURE project has evaluated the benefits of V2X communication in 15 high-risk driving scenarios [30]. These findings provide a valuable foundation for defining high-impact situations in which transmitting specific information is strongly justified. If a transmitting vehicle can recognize such scenarios in real time, it can dynamically adapt its communication behavior to match the inferred safety requirements of the environment. This enables a context-aware, safety-driven communication policy that prioritizes messages when and where they are most likely to reduce risk. Importantly, this approach does not require modeling the receiver's decision-making process directly. Instead, it justifies information sharing based on the expected safety benefit of transmission, as inferred from the scenario.

By grounding message generation in accidentology results, this approach provides a pragmatic and risk-informed framework for collaborative perception in vehicular networks.

To illustrate this, let us consider the scenario illustrated in

Figure 1. A vehicle (V1) is positioned on the left side of a straight road, while a pedestrian (P1) is crossing, and another vehicle (V2), approaching from the right, is obscured by a bus (O1). This hidden pedestrian situation is particularly critical for accident prevention [30], highlighting the importance of collaborative perception between vehicles.

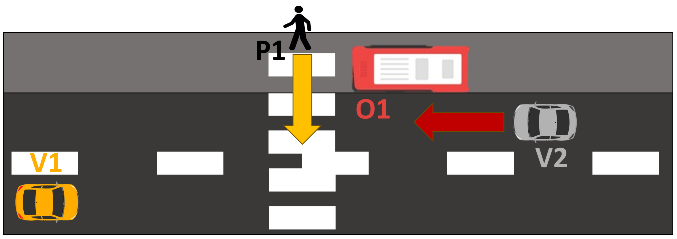

Figure 1. Use Case: Hidden Pedestrian Intending To Cross.

This use case illustrates a fundamental limitation of conventional CPS when operating in safety-critical contexts. Traditional systems, which lack the ability to interpret the situational context, must manage a trade-off between communication frequency and channel load. In the absence of contextual understanding, these systems are unable to determine which road user information should be prioritized. As a result, they often resort to broadcasting all detected objects at a high frequency to ensure that actionable information is delivered promptly.

However, such an approach can be counterproductive. In situations where not all information is relevant, as illustrated by the unnecessary transmission of bus data in this scenario (see Figure 1), the additional communication load increases channel congestion and latency. This, in turn, delays the delivery of critical information, diminishing its impact. Consequently, the receiving vehicle (V2) may be unable to make timely and appropriate decisions, thereby increasing the risk of collision or unsafe behavior.

These limitations emphasize the need for a context-aware and adaptive communication strategy, one that can recognize high-risk situations and dynamically modulate the information-sharing rate based on inferred safety requirements. By tailoring the communication to the situational context, the system can achieve both high efficiency and improved safety performance, avoiding the pitfalls of channel overload or under-communication during critical moments.

A promising solution involves the integration of a formalized and shared knowledge base within communicating vehicles. In this approach, the sender vehicle (V1) can selectively transmit only the most semantically relevant and safety-critical information, such as the detection of a hidden pedestrian, while the receiver (V2), equipped with an aligned knowledge representation, is capable of interpreting the data with greater accuracy and urgency. This knowledge-driven communication paradigm facilitates a more intelligent and context-sensitive collaborative perception framework, ultimately enhancing decision-making capabilities and improving safety in complex traffic environments.

IV. Understanding the Driving Scene

A. *Formalizing concepts*

Ontologies—structured models in knowledge representation—enable this level of contextual relevance by defining sets of concepts, their attributes, and relationships within a specific domain [31–34]. Leveraging ontologies enables machines to process and share information with enhanced semantic precision. In autonomous vehicle systems, ontologies provide a standardized framework for consistently interpreting and integrating data across diverse systems—an essential capability for effective inter-vehicular communication and decision-making. Given the variety of data sources in autonomous driving, from real-time sensors to camera feeds, ontological mapping transforms raw data into semantically enriched formats.

To capture the complexity of the driving environment, we used two interlinked ontologies [35]. The first, the *Road Topology Ontology*, formalizes the physical and regulatory structure of the road network. The second, the *Agent Ontology*, models road users, their behaviors, interactions, and visibility conditions. At runtime, a knowledge graph is constructed by instantiating these ontologies using real-time perception data, enabling semantic reasoning for context-aware decision-making.

The complete class and property definitions of both ontologies are provided in the Annex (Table I–Table IV).

B. *Building the Knowledge Graph*

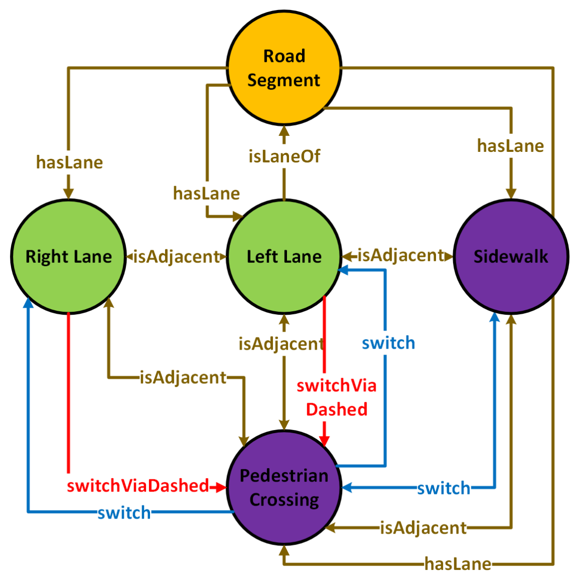

Figure 2. Representation of the road topology for the use case.

The construction of the knowledge graph begins with modeling the *road topology*, which captures the structural layout and regulatory logic of the driving environment. This includes the relationships between `Lanes`, `Intersections`, `PedestrianCrossings`, and turn directions, as well as control elements such as `TrafficLights` and `LaneRestrictions`.

These concepts are formalized through a dedicated *Road Topology Ontology*, which defines not only the static geometric entities but also their topological and regulatory interconnections using semantically meaningful properties such as `hasLane`, `isConnected`, `hasTurnDirection`, and `switchViaIntersection`.

As shown in Figure 2, the resulting topology graph provides a static, machine-interpretable representation of the road network, where each `RoadSegment`, `Lane`, and `PedestrianCrossing` is instantiated and connected according to the real-world configuration. This component may be precomputed and retrieved from a high-definition map or a dedicated infrastructure knowledge base. The ontology also supports rule-based reasoning, such as inferring priority relationships at intersections or determining occlusion risks based on spatial adjacency and lane layout.

The second step involves populating the graph in *real time* with dynamic information about road users and their observed behaviors. These agents—such as vehicles, pedestrians, and cyclists—are integrated into the knowledge graph using a separate *Agent Ontology*, which models classes of road users, their actions (e.g., `Accelerating`, `Stopping`, `Walking`), their positions, and their interactions. This dynamic content is derived from onboard sensors as well as received CPMs and is expressed as semantic triples, enabling structured querying and logical inference.

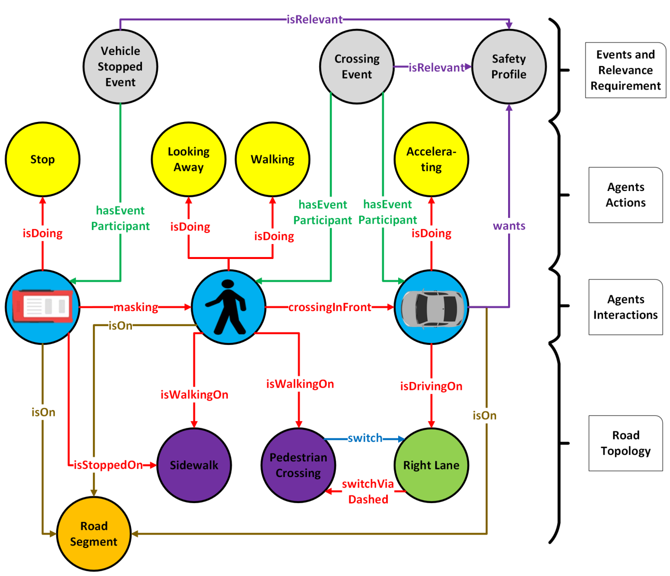

Figure 3. Example of a full Knowledge Graph for the use case, including topology and agent interactions.

Figure 3 illustrates the resulting integrated knowledge graph. Static elements (e.g., lanes, sidewalks, crossings) are semantically linked to dynamic agents (e.g., vehicles driving on specific lanes, pedestrians crossing a road). These links enable high-level reasoning about the scene, including interaction detection, right-of-way analysis, and occlusion inference.

Once the knowledge graph is populated with both the *road topology* and the *agent state and behavior*, the system can assess the relevance of specific observations by detecting contextually significant or safety-critical situations. This process, described in Section V, forms the basis for generating semantically filtered, high-utility CPMs tailored to the needs of receiving agents.

V. Contextual Relevance Estimation

Relevance identification is achieved by recognizing high-risk interactions between road users. The first step for the transmitting vehicle is to reason over its local knowledge in order to extract safety-critical events.

A. Extracting High-Risk Interactions

High-risk interactions are detected through a reasoning layer that applies a set of logical rules written in the Semantic Web Rule Language (SWRL). These rules operate over an ontological representation of the driving scene, enabling the system to infer new knowledge from the existing structure of spatial, temporal, and behavioral data. SWRL rules follow a declarative logic-based format, composed of antecedents (conditions) and consequents (inferred facts), all expressed using the vocabulary of the domain ontology — including classes (e.g., `Vehicle`, `Pedestrian`), properties (e.g., `isOn`, `crossingInFront`), and relationships between entities.

This formalism provides a powerful mechanism for modeling and identifying semantically meaningful interactions within a scene. For instance, a rule can infer that a `CrossingEvent` is occurring when a vehicle is maintaining speed while a pedestrian is crossing its path under specific structural and behavioral conditions. Such inferences form the basis for determining whether a given situation constitutes a safety-critical event that should be communicated to interested agents. Scenario-specific rules focus on clearly defined use cases where the benefits of collaborative perception have been observed or demonstrated. These rules capture high-risk interactions such as unprotected left turns across oncoming traffic, merging at blind intersections, or pedestrian crossings obscured by static obstacles — scenarios in which an individual vehicle's perception is likely to be limited and where shared context can meaningfully improve situational awareness [30]. Although highly effective within their intended scope, these rules tend to be less robust when applied to unforeseen scenarios or rare combinations of factors not considered during their formulation. Despite the limitations of scenario-specific rules, they still provide valuable semantic structure for decision-making. Importantly, the presence of a matching rule does not imply that all other cases are irrelevant. In real-world driving, unexpected interactions often emerge from uncommon combinations of seemingly benign factors. Therefore, the system should not rely solely on exact rule matching but instead assess the semantic similarity of a current situation to known risk patterns. This can be achieved by reasoning over the ontological structure or via similarity-based approaches in the embedding space of scene descriptors.

To extend the expressiveness and adaptability of the system, an alternative is to leverage accidentology databases. By analyzing large-scale, annotated records of traffic accidents, machine learning techniques can be used to discover implicit relevance patterns — correlations between agent behavior, environmental context, and collision likelihood [31][32]. These insights can be distilled into either: Parameterized conditions that inform new SWRL rules, or direct rule generation pipelines, where learned decision trees or classifiers are translated into rule sets. Such rules are not only more specific but also adaptive, allowing the system to evolve over time as more accident data becomes available. The training process serves as a bridge between raw statistical correlations and structured, interpretable knowledge. Once trained, the vehicle can assess the relevance of a situation in real time by applying the generated SWRL rules to its local representation of the scene — continually updated through its onboard perception stack and shared knowledge modules.

B. Example Rule: Crossing Event Detection

In the pedestrian crossing scenario, we can define a SWRL rule to detect and infer the relevance of such an event, as shown below:

Crossing Event Detection Rule

```
IF:
  Vehicle(?lowPriority) ^
  RoadUser(?highPriority) ^
  RoadSegment(?road) ^
  isOn(?lowPriority, ?road) ^
  isOn(?highPriority, ?road) ^
  Lane(?lowPriorityLane) ^
  isDrivingOn(?lowPriority, ?lowPriorityLane) ^
  Lane(?highPriorityLane) ^
  (isDrivingOn(?highPriority, ?highPriorityLane)
   OR isWalkingOn(?highPriority, ?
       highPriorityLane)) ^
  crossingInFront(?lowPriority, ?highPriority) ^
  (switchViaDashed(?lowPriorityLane, ?
      highPriorityLane)
   OR (switchViaTrafficLight(?lowPriorityLane, ?
       highPriorityLane) ^
      hasTrafficLight(?lowPriorityLane, ?
          trafficLight) ^
      hasTrafficSignalPhase(?trafficLight, ?
          phase) ^
      sameAs(?phase, Red))
   OR switchViaIntersection(?lowPriorityLane, ?
       highPriorityLane)) ^
  isDoing(?lowPriority, ?action) ^
  (sameAs(?action, Accelerating)
   OR sameAs(?action, MaintainingSpeed))

THEN:
  CrossingEvent(?crossing) ^
  hasEventParticipant(?crossing, ?lowPriority) ^
  hasEventParticipant(?crossing, ?highPriority)
```

This SWRL rule identifies a crossing event involving a low-priority vehicle and a higher-priority road user (such as a pedestrian or another vehicle) when specific spatial and behavioral conditions are met within a driving scene. The rule applies when both agents are present on the same road segment, each traveling on a distinct lane. The high-priority user is either driving or walking on their lane, while the low-priority vehicle is in a situation where the two lanes are linked—meaning a lane change or crossing is structurally possible—either via a dashed line, a traffic light (which is currently red for the low-priority vehicle), or an intersection. Furthermore, the higher-priority user is observed to be crossing in front of the vehicle, indicating a potential interaction. Despite this, the vehicle is accelerating or maintaining its speed, which contrasts with the expected behavior in such a scenario, where the vehicle should slow down due to its lack of priority. Given these conditions, the rule infers the existence of a `CrossingEvent`, linking both agents as participants, and potentially signaling a conflict or risk that needs to be addressed in downstream reasoning or decision-making processes.

C. Determining Receiver Relevance

Once a safety-critical event has been inferred, the next step is to assess whether any connected agents in the vicinity should be informed. Relevance is not solely determined by the severity of the event itself, but also by the contextual usefulness of the information to a potential receiver. This dual perspective — sender-side significance and receiver-side utility — enables efficient and targeted communication in collaborative perception systems.

Receiver relevance is evaluated through reasoning and querying mechanisms over the shared semantic knowledge base. A SPARQL query can be issued to identify nearby connected agents that satisfy two key conditions:

1) **Capability:** The agent must be technically able to receive and interpret the message, i.e., it is a connected agent with the adequate support.
2) **Contextual Awareness:** The agent must be in a situation where the received information could affect its decision-making process or enhance its situational awareness.

In practice, this assessment involves evaluating spatial, temporal, and behavioral factors for each agent in the vicinity. For example, a *pedestrian crossing* event is highly relevant to a vehicle approaching the crossing from the same or an intersecting road segment, as it may need to slow down or stop. However, it is largely irrelevant to a vehicle moving away from the area or traveling on a disconnected or parallel segment.

To support this reasoning, all participants involved in an event are explicitly linked to it using the `hasEventParticipant` property. This semantic relationship ensures that the presence of at least one connected participant in a critical interaction can trigger message generation. In the pedestrian crossing scenario, for instance, if a connected vehicle is involved (as the lower-priority participant), the system infers that information about the other participant (e.g., a pedestrian) should be included and prioritized in the transmitted message.

Conversely, in a the use case, the bus (O1) parked on the sidewalk may trigger a `StoppedVehicle` event. However, this event is only considered relevant to vehicles driving on the same lane, who might need to change lanes, slow down, or adapt their trajectory. Even if a connected vehicle (e.g., V2) is present in the scene, it is located on a different lane that making the information about the bus under-prioritized. This approach avoids unnecessary communication overhead and ensures that bandwidth is preserved for information with immediate operational value.

VI. Knowledge Sharing

Knowledge sharing between vehicles complements local sensor data by providing additional context, which is essential for autonomous decision-making. Studies have shown that ontologies and formalized knowledge representations significantly enhance the decision-making capabilities of automated systems [33][34][36]. Semantic-aware messages allow vehicles to exchange not only raw data but also high-level, structured information about their environment [19–21][24][25].

To enable the sharing of semantically relevant content, the CPM format can be extended to incorporate semantic properties. Unlike conventional CPMs that transmit raw object-level data (e.g., positions and velocities), Semantic CPMs (S-CPMs) include structured annotations grounded in a shared ontology. This enables vehicles to encode both the "what" (e.g., a pedestrian at position X) and the "why it matters" (e.g., "pedestrian hidden from eastbound traffic, located on sidewalk, and likely to cross").

In the presented use case, vehicle V1 constructs a local knowledge graph and identifies a `CrossingEvent` involving a pedestrian obscured by a bus (O1). The onboard reasoning system determines that vehicle V2, approaching from the opposite direction with no line of sight, would benefit from this information. Consequently, V1 transmits an S-CPM enriched with semantic annotations, such as the masking relationship between the bus and the pedestrian or the pedestrian's location on the sidewalk.

This concise yet semantically rich message allows V2 to interpret the situation even without direct visual contact, enabling faster and more informed reactions.

Figure 4 illustrates how the semantic layer is integrated into the traditional CPM pipeline. On the left, sensor inputs from local perception modules and received CPMs are used to populate a knowledge graph where entities, actions, and relationships are semantically defined (cf. Section IV). A reasoning engine then operates over this graph to infer high-risk events, such as a `CrossingEvent` involving a hidden pedestrian (cf. Section V).

When a safety-relevant situation is inferred, the system evaluates whether any nearby connected agents would benefit from the information. If so, it constructs an S-CPM that includes only the contextually relevant semantic content, as shown on the right side of the diagram. This message is transmitted over the V2X channel, allowing the receiving vehicle to understand the event without reconstructing the entire scene from raw data.

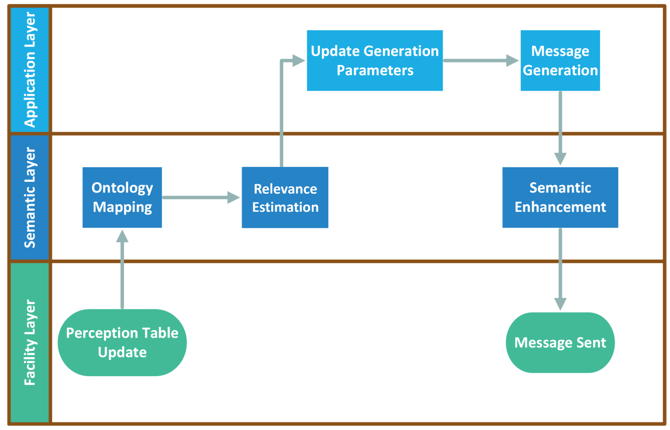

Figure 4. Integration of Semantic Layer for CPM.

This architecture tightly integrates perception, reasoning, and communication by embedding semantic understanding into the message-generation pipeline. It shifts the paradigm from periodic, raw data transmission to the sharing of selectively filtered, semantically prioritized, and meaning-rich content.

VII. Discussion

The proposed framework introduces a semantically enriched, context-aware communication mechanism for vehicular networks, aiming to transmit only the most relevant information to downstream agents. While the architecture demonstrates promising potential for reducing channel load and enhancing safety, several key issues must be considered for real-world deployment.

A. Generalization Beyond Rule-Based Reasoning

Our approach currently relies on manually crafted SWRL rules to detect high-risk interactions. While this ensures transparency and interpretability, it limits the system's adaptability to unexpected or complex scenarios not captured by predefined logic. Human-authored rules are also labor-intensive to maintain and susceptible to obsolescence as traffic environments evolve.

To address this, future developments should incorporate data-driven approaches such as decision tree induction or statistical relational learning to automatically derive semantic rules from annotated driving datasets. These methods have been successfully applied in other fields to generate interpretable knowledge bases [14], and could help enhance generalization in dynamic environments.

B. Real-Time Reasoning and Scalability Constraints

Ontologies provide rich structure but incur computational overhead during reasoning and querying. Inference over large-scale knowledge graphs in real time remains challenging, especially under V2X latency constraints (typically <100 ms per CPM cycle).

To mitigate this, techniques such as incremental reasoning, reasoning over lightweight ontology subsets, or offloading to roadside infrastructure may be required [34][36]. The feasibility of these methods in realistic urban traffic conditions must be quantitatively evaluated through simulation and profiling experiments.

C. Knowledge Graph Requirements and Semantic Interoperability

The effectiveness of the proposed semantic communication framework relies on each agent's ability to access and reason over a structured knowledge graph representing its local environment. However, this requirement introduces significant challenges for real-world implementation. In a collaborative setting, the utility of semantically enriched messages depends on the receiver's capacity to correctly interpret the transmitted content—something that is only feasible if both sender and receiver share not only common ontological definitions but also compatible graph structures.

This dependency presents a barrier to semantic interoperability in practical deployments. Discrepancies in class hierarchies, naming conventions, or modeling assumptions can result in semantic mismatches or the misinterpretation of critical safety messages. For instance, the semantics of a `CrossingEvent` or `Occlusion` may differ in granularity or causal meaning across implementations, even when referring to the same real-world observation.

To address this, recent initiatives have introduced ontology standards to support semantic alignment. ETSI's SAREF4Automotive ontology [37] extends the SAREF (Smart Applications REFerence) framework to describe key automotive concepts such as vehicle status, driving modes, and environmental features in a machine-interpretable way. Likewise, the W3C Semantic Sensor Network (SSN) and its lightweight core, SOSA (Sensor, Observation, Sample, and Actuator) [38], offer an ontology stack for modeling sensors, observations, and actuators.

While these ontologies provide a valuable foundation, they currently lack explicit support for behavior- and event-centric modeling required in collaborative perception tasks, such as interaction between agents, priority inference, or semantic occlusion reasoning. Bridging this gap will require extending or aligning these standards with richer ontologies that capture the spatio-temporal and causal dynamics of road scenes. A long-term solution may involve developing a modular and extensible ontology framework where standardized core concepts are combined with domain-specific modules tailored to V2X semantic communication.

D. Integration with Planning and ADAS Systems

Currently, the semantic layer focuses on perception-level reasoning. However, its benefits extend further downstream. Integrating semantic information into behavior planning or trajectory generation modules can enable more proactive and interpretable decision-making [26][27].

For example, a `CrossingEvent` involving a pedestrian could trigger adaptive speed control or early braking in an ADAS module, even before visual confirmation is available. Future work should explore pipeline integration and quantify decision quality improvements.

E. Communication Policy and Network Efficiency

By prioritizing relevant messages, the framework also acts as a semantic-aware congestion control mechanism. This aligns with recent works in context-aware message generation such as Direct-CP [16] and Where2Com [17], but introduces a more explicit semantic reasoning layer. However, network-level performance metrics such as bandwidth usage, packet delivery ratio, and channel congestion under high vehicle density must be evaluated to confirm expected efficiency gains. Additionally, fallback mechanisms—such as periodic CPMs or redundant messages in safety-critical scenarios—should be designed to ensure robustness under communication loss or partial knowledge graph failures.

F. Ethical and Privacy Considerations

Semantic communication inherently transmits high-level interpretations of behavior and intent. While beneficial for decision-making, this raises privacy and ethical concerns. For instance, sharing a message stating that a pedestrian is likely to cross constitutes behavioral profiling. If transmitted over unsecured channels, this information could be exploited or misused. Ensuring compliance with privacy regulations such as GDPR requires anonymization, and minimization. Moreover, inference confidence scores or uncertainty annotations may help mitigate the impact of incorrect or spurious reasoning.

VIII. Conclusion

This work introduces a semantic communication framework for collective perception that prioritizes the transmission of contextually relevant information through ontological reasoning. By leveraging structured knowledge graphs and logical inference, the system identifies high-risk interactions and generates semantically enriched CPMs that improve the precision and utility of shared information. Beyond reducing communication overhead, this approach enhances safety in occluded or complex environments by enabling proactive and informed decisions. In future work, relevance estimation will be implemented within a simulation environment, leveraging ontologies to support various consumers, such as Perception, Advanced Driver Assistance Systems (ADAS), and Automated Driving. This effort will involve the development of an ontology-based framework and a comparative analysis of two distinct approaches to defining relevance. The first approach will utilize machine learning algorithms for pattern extraction, employing data-driven techniques to derive relevance rules. The second approach will adopt a scenario-specific exploration, where relevance is defined based on predefined scenarios and expert-driven criteria tailored to specific use cases. By comparing these methods, this study aims to uncover their respective strengths, limitations, and areas of applicability, paving the way for more adaptive and effective relevance estimation strategies across diverse applications. Additionally, comparisons will be made with methodologies presented in recent literature [15][16][17] to benchmark and validate the proposed approaches. It is also crucial to address the challenges posed by ontology computation in real-time scenarios, ensuring its feasibility and robustness in practical implementations.

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APPENDIX

ANNEX: ONTOLOGY SPECIFICATIONS

TABLE I. ONTOLOGY CLASSES – ROAD TOPOLOGY

Class	Description
RoadElement	
RoadSegment	A segment of the road, describing topographical proximity.
Intersection	A specific RoadSegment which describes the intersection between two or more RoadSegments.
Lane	A designated path describing topological proximity.
MergingLane	A subclass of Lane.
Sidewalk	A subclass of Lane which is a pedestrian path along the side of a road.
PedestrianCrossing	A subclass of Lane which designates areas for pedestrians to cross the road safely.
ParkArea	An area intended for parking vehicles.
Traffic Management	
TrafficLight	A signaling device used to control vehicle and pedestrian traffic.
LaneRestriction	A constraint or rule that limits how a lane can be used.
Carpooling	A subclass of LaneRestriction. Restriction allowing only high-occupancy vehicles in a lane.
Closed	A subclass of LaneRestriction. Indicates a lane that is temporarily or permanently inaccessible.
VehicleType	A subclass of LaneRestriction. Indicates the authorized vehicles (e.g., bus, bike).
TurnDirection	Represents a direction that a vehicle is allowed to take when leaving this lane.
Left, Right, Front, Back	Specific subclasses of TurnDirection.
Environmental Context	
NonRoadElement	An urban element not forming part of the road (e.g., buildings, trees).

TABLE II. ONTOLOGY PROPERTIES – ROAD TOPOLOGY

Property	Description
RoadElement Properties	
hasLength	Describes the length of a RoadSegment.
hasLane	Relates a RoadSegment to a Lane.
hasIntersection	Describes the relationship between a RoadSegment and an Intersection.
hasSidewalk	Links a RoadSegment to a Sidewalk.
Traffic Management Properties	
hasLaneRestriction	Relates a Lane to a LaneRestriction.
hasTrafficLight	Links a RoadSegment to a TrafficLight.
hasTurnDirection	Relates a Lane to a TurnDirection.
isLaneOf	Relates a Lane to a RoadSegment.
isAdjacent	Describes the adjacency of two Lanes.
isConnected	Indicates whether two RoadSegments are connected.
Environmental Context Properties	
hasNonRoadElement	Links a RoadSegment to NonRoadElements like trees or street furniture.
Intersection Properties	
incomingLane	Links an Intersection to an incoming Lane.
outcomingLane	Links an Intersection to an outcoming Lane.
Switching Properties	
switchVia	Relates a Lane to another Lane via a switching route.
switchViaDashed	A specific case of switchVia, where the route is dashed.
switchViaIntersection	A specific case of switchVia, involving a switch at an Intersection.
switchViaStop	A specific case of switchVia, involving a stop.
switchVia TrafficLight	A specific case of switchVia, involving a traffic light.

TABLE III. ONTOLOGY CLASSES – AGENTS

Class	Description
Road Users	
RoadUser	Any participant in road traffic.
Vehicle	A subclass of RoadUser representing motorized vehicles.
ConnectedCar, EmergencyVehicle, Bus, Car, Truck	Specific types of Vehicle.
NonVehicle	A subclass of RoadUser representing non-motorized or non-mechanical entities.
Animal, Cyclist, Pedestrian	Specific types of NonVehicle.
Actions	
Action	A generic action performed by a RoadUser.
PedestrianAction	Actions specific to Pedestrian and Cyclist.
LookingAway, LookingRoad, Lying, Walking, Standing	Specific types of PedestrianAction.
VehicleAction	Actions specific to Vehicle.
ToLeftChange, ToRightChange, Accelerating, Decelerating, MaintainingSpeed, Stopping, TurningLeft, TurningRight, UTurn	Specific types of VehicleAction.
Profiles	
Profile	Specifies the information required from the CPM for a ConnectedCar.

TABLE IV. ONTOLOGY PROPERTIES – AGENT INTERACTIONS

Property	Description
RoadUser Actions	
isDrivingOn	Associates a Vehicle with the Lane it is driving on.
isStoppedOn	Associates a Vehicle with the Lane it is stopped on.
isWalkingOn	Associates a NonVehicle with the Lane it is walking on.
crossingInFront	Indicates that a NonVehicle is crossing in front of a Vehicle.
isDoing	Indicates the Action being performed by a RoadUser.
Visibility Properties	
masking	Indicates that a Vehicle or NonRoadElement obstructs the view of a RoadUser.
hasVisibility	Specifies that a Vehicle has visibility of a given RoadUser.
hasNoVisibility	Specifies that a Vehicle does not have visibility of a given RoadUser.
Event Participation	
hasEventParticipant	Associates an Event with the RoadUser(s) involved.
isParticipantOf	Links a RoadUser to the Event in which they participate.
Profile Properties	
wants	Associates a ConnectedCar with a Profile specifying CPM-related requirements.
isRelevant	Links an Event to a Profile if the event is relevant to that profile.