Context-Aware Collaborative Perception: Estimating Relevance through Knowledge Representation

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***Abstract*—Automated driving systems have made significant strides in real-time perception and response to complex driving scenarios. However, these systems struggle when road users are beyond sensor range or obstructed by obstacles, limiting their ability to make informed decisions. Cooperative Intelligent Transport Systems (C-ITS) offer a promising solution by enabling vehicles to share real-time data with nearby vehicles and infrastructure. While this enhances collaborative perception, a major challenge is managing the high volume of sensor data exchanged, which are not always useful for the receiver. This can lead to data congestion, latency, and misinterpretation. Our solution addresses these issues by using an ontology to represent a vehicle's observable scene and assess information relevance. Additionally, the ontology serves as a knowledge base, facilitating semantic communication that allows more effective interpretation of received messages. This approach aims to improve both the safety and efficiency of cooperative systems in automated driving environments.**

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

I. INTRODUCTION

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 [1], 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 [2][3]. To address these limitations, C-ITS have emerged as a promising solution [4]. 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 [5][6]. 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 challenges in merging data across heterogeneous sources.

In the context of vehicular networks, effective communication hinges on the principle of transmitting relevant information efficiently, as conceptualized by Shannon's Information Theory. According to Shannon, information is defined as the reduction of uncertainty (entropy) [7][8]; thus, relevant data in vehicular systems is the one that significantly contributes to reducing uncertainty about the environment for the receiving vehicle. In this case, data relevance is not merely about the volume of information but about the usefulness of the transmitted data regarding the needs of the receiver. In CPM, the relevance of information is closely tied to the type of system consuming it and its specific context. For instance, an Automatic Emergency Braking (AEB) system requires highly precise data regarding very close predicted object trajectories to make immediate safety interventions; An Autonomous Driving (AD) system needs a broader understanding of the environment to plan longer-term maneuvers, such as anticipating the pedestrian's intention to cross the road. The solution utilizes an ontology to represent the vehicle's observable scene, enabling it to assess the relevance of the situation. This allows the system to adjust the frequency and priority of message transmissions according to its criticity. By enhancing semantic precision and contextual relevance, this approach aims to reduce data congestion, improve decision-making efficiency, and ultimately advance the safety and efficacy of C-ITS.

This paper is organized as follows: Section II provides an overview of congestion mitigation in Collaborative Perception and Semantic Communication. Section III presents a specific use case to introduce the issues of contextual and informational relevance. In Section IV, an ontology model is explored to describe the vehicle's knowledge base. Section V then discusses methods for using the ontology to assess the contextual relevance of situations. Finally, Section VI demonstrates how this knowledge can be shared among connected vehicles and integrated into the vehicle's C-ITS architecture.

II. Related Work

Mitigating channel congestion has been the main concern in a large number of research activities. For example, in [9], 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 [10]–[13]. 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, [14] 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 [14]. Consequently, other studies propose limiting communication within geographical zones to ensure a level of relevance. In Direct-CP [15], collaborative communication is monitored by infrastructure based on each vehicle's maneuver intent. In contrast, Where2Com [16] 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, [17] 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 [18], 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 [19]–[22] where a semantic encoder/decoder achieves higher transmission efficiency. This approach is demonstrated in [23] 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, [24] 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. Assessing Relevance

Let us imagine a scenario as shown in Figure 1. A vehicle (V1) is positioned on the left side of a straight road, while a pedestrian (P1) crosses the road, and a vehicle (V2) on the right is masked by a bus (O1). This "hidden pedestrian" situation is critical for accident prevention [25], emphasizing the need for collaborative perception between vehicles. In traditional CPS, V1 continually generates CPMs without fully accounting for the specific environmental context. While such messages are situationally relevant, they usually include pre-processed sensor data on all detected objects, such as their positions, speeds, and types. Consequently, the message would

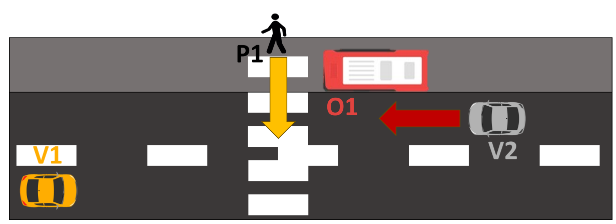

Figure 1. Use Case : Hidden Pedestrian Intending To Cross.

relay information about the pedestrian (P1), the bus (O1), the vehicle (V2), data that may not be entirely relevant to the vehicle (V2). This lack of context-awareness can lead to the transmission of unnecessary data, potentially impacting decision-making and response times. A more efficient solution involves integrating formalized knowledge into both vehicles. This way, the vehicle (V1) can communicate only the most valuable and situationally relevant information, while the other vehicle (V2), armed with a similar knowledge base, can interpret the context and make quicker decisions.

IV. Formalizing Knowledge

Ontologies—structured models in knowledge representation—enable this level of contextual relevance by defining sets

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of concepts, their attributes, and relationships within a specific domain [26]–[29]. 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. For example, to resolve the relevance assessment in the masked pedestrian scenario, an ontology must efficiently describe the situation. Here, the *Road-Segment* comprises two *Lanes* (*Lane-Left* and *Lane-Right*) and a *Crossing-Path*. *Vehicle-1*, classified as a *Car*, *isDriving* on *Lane-Right* and *hasDetected Vehicle-2*, *Pedestrian-1*, and *Bus-1*. Meanwhile, *Pedestrian-1 intendToCross* via the *Crossing-Path*. *Vehicle-2*, also a *Car*, *isDriving* on *Lane-Left* and *hasDetected Vehicle-1* and *Bus-1* and also *intendToCross* via the *Crossing-Path*. This ontological

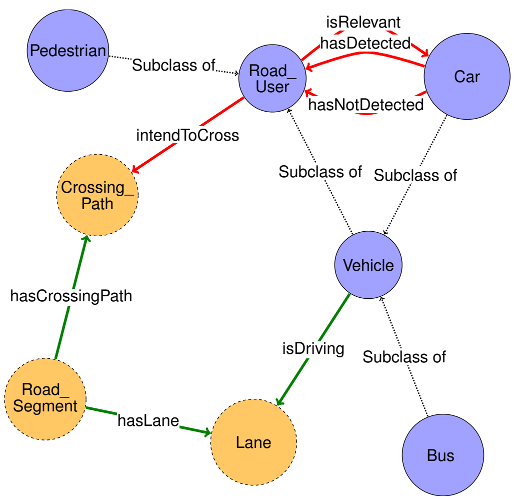

Figure 2. Example Ontology for Masked Pedestrian Use Case.

(Figure 2) representation of the scene allows the system to capture structural properties (green arrows) and functional properties (red arrows), supporting collaborative perception and enhancing safety-critical decisions.

V. Contextual Relevance Estimation

Relevance identification is performed by establishing a set of rules in the Semantic Web Rule Language (SWRL) format, which facilitates advanced reasoning over ontologies to infer new knowledge from existing information. SWRL rules consist of conditions and conclusions expressed in terms of ontological classes and properties, allowing for the formal representation of complex relationships and logical inferences. These rules can adhere to theoretical principles, defining relevance based on parameters, such as distance, state, or type, thereby creating a structured approach to understanding interactions within a given context. Alternatively, they can be scenario-specific, tailored to reflect particular conditions and requirements relevant to specific situations. Scenario-based relevance can be derived from accidentology studies that identify scenarios where the safety benefits of C-ITS have been demonstrated [25]. The SECUR results distilled 15 high-risk scenarios, with safety benefits estimated for each. Thus, relevance estimation can be achieved through scene recognition by determining if the vehicle's observable scene falls within a high-risk scenario. Scenario-based relevance, relies on predefined cases that may not generalize well to novel or evolving traffic situations. This approach risks overlooking edge cases or unexpected factor combinations that do not neatly fit within established categories but still pose safety concerns. Despite this, a scenario-specific definition ensures that information is relevant within the identified use cases but does not inherently imply irrelevance in other scenarios. In practice, a message deemed crucial in one context may still hold value in different, yet unaccounted-for, situations. Thus, rather than strictly matching predefined cases, it may be necessary to assess the degree to which the vehicle's current situation resembles known scenarios.

Another solution could be to find patterns from accidentology databases itself by employing machine learning techniques [27][26], to derive complex SWRL rules that are highly specific and adaptive to real-world conditions (see Figure 3). In this context, machine learning models not only facilitate the

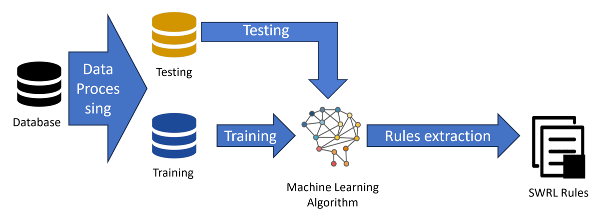

Figure 3. Rules Extraction Based On Accidentology Database.

extraction of patterns and trends from historical accident data but also enhance the precision of the SWRL rules generated. This integration allows for a continuous improvement loop, where the relevance criteria can evolve based on updated data inputs. After a training phase, the vehicle becomes capable of assessing the relevance of a situation in real time by using the ontology, which is updated through vehicle's perception layer, and by applying the SWRL rules. For each road users instantiated inside the knowledge base, the relevance is assessed in relation to the other road users.

For the pedestrian use case, we can define a simple SWRL rule to infer the relevance of the situation.

$$\begin{aligned}
&\text{RoadUser}(?pedestrian) \wedge \text{Car}(?car) \\
&\quad \wedge \text{intendToCross}(?pedestrian, ?crossing) \\
&\quad \wedge \text{intendToCross}(?car, ?crossing) \\
&\quad \wedge \text{hasNotDetected}(?car, ?pedestrian) \\
&\quad \wedge \text{speed}(?car, ?carSpeed) \\
&\quad \wedge \text{swrlb:greaterThan}(?carSpeed, \text{SpeedThreshold}) \\
&\ \rightarrow \text{isRelevantTo}(?pedestrian, ?car)
\end{aligned}$$

This set of rules defines when a road user is considered relevant to a vehicle. Specifically, it evaluates whether both a pedestrian and a vehicle intend to cross paths and ensures that the vehicle has not yet detected the pedestrian. It also checks the vehicle's speed against a predefined threshold, indicating that if the vehicle is already stationary, the information is not relevant. If these conditions are satisfied, the pedestrian data becomes relevant to the vehicle, prompting any vehicle that has locally-detected both elements to include the relevant information in a CPM.

VI. Knowledge Sharing

Knowledge sharing between vehicles can complement sensor data by providing additional context, which is critical for autonomous vehicles. Studies show that ontology and formalized knowledge representation improve decision-making [28]–[30]. Semantic-aware messages can be used to share knowledge between vehicles, adding valuable semantic details about the environment [18]–[20][23][24]. For example, in this use case, sender can generate a message about the pedestrian not just with its position, speed, and timestamp but also enriched with semantic details like "pedestrian on sidewalk," "pedestrian intending to cross," or "pedestrian hidden by bus." This enriched information allows the receiver vehicle to fuse data from multiple sources, such as RSUs and other vehicles, recognizing that they have detected the same pedestrian, even if the detection timing and precision differ.

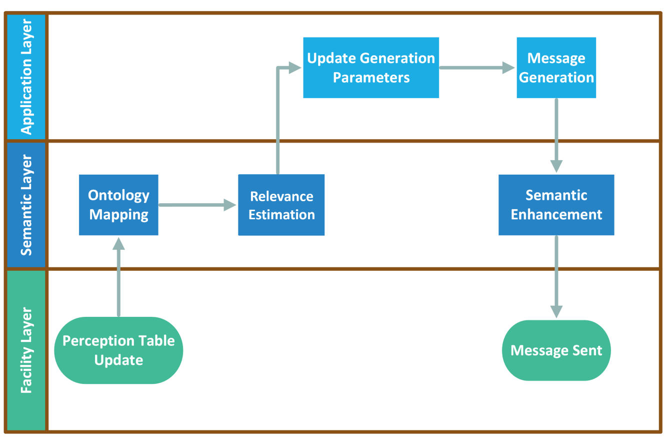

Figure 4. Integration of Semantic Layer For CPM.

In this use case, the vehicle (V1) observes a pedestrian (P1) crossing a straight road while a bus (O1) occludes another vehicle (V2) on the opposite side. The process begins with V1's sensors detecting and classifying entities within its environment. These entities—such as "Pedestrian", "Bus", "Crossing path", and "Vehicle"—are instantiated within the ontology (Ontology Mapping, Figure 4), each associated with specific properties like location, movement direction and link between instances (Section IV). Once these instances and properties are mapped in the ontology, an inference engine applies predefined rules to evaluate the scenario, SWRL rules (Section V) specify conditions under which an information relative to an element is relevant to another element (Relevance Estimation, Figure 4). Following this, the Collective Perception Application constructs a CPM containing only the relevant information, specifically prioritizing details about the pedestrian due to its potential impact on V2. Furthermore, the Collective Perception Application (CPA) dynamically adjusts the message transmission frequency based on the overall relevance of the situation. Based on the ontology instances and the sensors data, CPM message is enhanced with semantic properties like "intending to cross" (Semantic Enhancement, Figure 4). Upon receiving the enriched CPM, V2 utilizes its own ontological model to interpret the semantic information embedded within the message. This process allows the vehicle (V2) to integrate the contextual details about the pedestrian with its existing sensor data, effectively enhancing its understanding of the environment. For instance, recognizing that a pedestrian is "intending to cross" prompts the vehicle (V2) to prioritize its own response strategy, potentially preparing to yield or adjust speed. This capability to process semantic enrichment ensures that the receiver vehicle can act promptly and appropriately, even in complex driving conditions where visual information is compromised. This approach improves situational awareness and supports more accurate interpretation of the environment, thereby enhancing the value of information.

VII. Conclusion

C-ITS and the integration of CPS mark a significant advancement in enhancing road safety. By fostering real-time communication among vehicles and infrastructure, the proposed solution addresses critical limitations associated with traditional automated driving systems, particularly in terms of situational awareness and decision-making. The utilization of ontologies and semantic communication enables vehicles to share contextually relevant and semantically enriched information, thereby reducing data congestion and improving the accuracy of interpretations in dynamic environments. This research underscores the importance of situational pertinence and the value of information in collaborative perception, paving the way for safer and more efficient transportation systems.

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, compar-

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isons will be made with methodologies presented in recent literature [14][15][16] 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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