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Design and implementation of algorithms for data prioritization and dissemination in autonomous vehicular networks

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Abstact

This thesis investigates the potential improvements in traffic awareness achieved by collaboration among autonomous vehicles (AVs) through cooperative perception. The goal is to minimize the amount of sensory data to be shared among AVs to achieve full perception of the environment, which is to detect all potential obstacles in the surroundings of the AVs. To achieve this, the study assigns priorities to the sensory data collected onboard the AVs by defining various scoring functions. The algorithm computes the relevance of the sensory data for the potential neighbours by evaluating the distance between the AVs and the obstacles, the relevance referred to the direction in which the receiver is proceeding and assessing the amount of useful information that can be retrieved from the sensory data. The performance of the proposed data dissemination algorithm is compared with some baseline schemes that do not implement prioritization and only transmit data as soon as they are generated. Our proposed algorithm aims to assess the value of information in relation to each receiver and to prioritize message transmission by the vehicle with the best-quality obstacle data. Simulation results demonstrate that our algorithm can reduce the number of transmissions that are required to achieve full perception, with minor degradation in terms of accuracy for the detected obstacles.

Sommario

Questa tesi analizza le possibili migliorie nella condivisione delle informazioni raccolte dai sensori dei veicoli autonomi (AV) attraverso la percezione cooperativa. L'obiettivo è ottimizzare la quantità di dati da scambiare tra i veicoli autonomi al fine di ottenere una comprensione completa dell'ambiente circostante, in particolare la rilevazione di tutti gli eventuali ostacoli presenti nelle vicinanze dei veicoli autonomi. Per raggiungere questo obiettivo, lo abbiamo assegnato delle priorità ai dati raccolti a bordo degli AV definendo diverse funzioni di valore. L'algoritmo calcola la rilevanza dei dati raccolti per i potenziali ricevitori valutando la distanza tra gli AV e gli ostacoli, la rilevanza riferita alla direzione in cui sta procedendo il ricevitore e valutando la quantità di informazioni utili che possono essere recuperate dai dati. Le prestazioni dell'algoritmo di diffusione dei dati proposto sono confrontate con alcuni schemi di base che non implementano la prioritizzazione e trasmettono i dati non appena vengono generati. L'algoritmo proposto mira a valutare il valore delle informazioni in relazione a ciascun ricevitore e a dare priorità alla trasmissione dei messaggi da parte del veicolo con i dati sugli ostacoli di migliore qualità. I risultati delle simulazioni dimostrano che il nostro algoritmo è in grado di ridurre il numero di trasmissioni necessarie per ottenere la piena percezione, con un minore degrado in termini di precisione degli ostacoli rilevati.

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Chapter 1

Introduction

1.1 Introduction and Motivation

In recent years, the automotive industry has experienced a significant transformation with the emergence of Autonomous Vehicles (AVs) and the integration of Cooperative and Intelligent Transportation Systems (C-ITSs). Equipped with advanced sensors, artificial intelligence, and cutting-edge computing capacity, AVs are positioned to redefine transportation as we know it. The use of these technologies in the context of automotive can lead to safer and more efficient traveling without human intervention.

The increasing number of vehicles on roads and rapid urbanization pose significant challenges to road safety and transportation system efficiency. According to the World Health Organization (WHO), over 1.2 million people die each year in road accidents, with a substantial 93.5% of all the incidents resulting from human error [1] [2].

These challenging situations require advanced solutions to improve road safety. A prerequisite for this is the design of new assistance systems with more capable sensor and information technologies, that can offer support on driving tasks and enhance overall driving safety [3]. Autonomous driving refers to the ability of a vehicle to operate with minimal (or no) human intervention and researchers predict that by 2025 we will see approximately 8 million autonomous or semi-autonomous vehicles on the road. [4]. The Society of Automotive Engineers (SAE) defines 6 levels of driving automation ranging from 0 (fully manual) to 5 (fully autonomous). Level 0 vehicles are manually controlled, requiring the driver to handle all aspects of driving. Moving to Level 1, we find basic driver assistance systems like cruise control, which assist with either steering or acceleration. Level 2 introduces advanced driver assistance systems (ADAS) capable of controlling both steering and acceleration. At Level 3, vehicles gain environmental detection capabilities and can make informed decisions independently, yet they still rely on human intervention in certain situations. Level 4 vehicles can intervene in case of system failure and operate autonomously in specific environments without requiring human input. Finally, Level 5 represents full driving automation, where vehicles can navigate all situations without human intervention, even in complex scenarios [5].

In order to be able to implement these functionalities, vehicles are equipped with different types of sensors, depending on the desired autonomous driving level. Autonomous vehicles above Level 3 are usually equipped with a multitude of sensors like Cameras, RADARs (Radio Detection and Ranging) and LIDARs (Light Detection and Ranging) which can perceive and understand the surrounding environment. However, this type of autonomous vehicles require continuous, real-time situational awareness of the surrounding environment, a concept referred to as ”cooperative perception” [6], which is difficult to achieve by only relying on the sensors onboard of the vehicle itself for the following reasons [7]:

- **Insufficient perception information:** autonomous vehicles use onboard sensors like LiDAR, cameras, and radars. Yet, it is hard to deal with the occlusion problem, in which an object, e.g. a building or obstacles, would block the environment sensing beyond it. Additionally, sensors are physically limited as they provide sparse and low-resolution data for long-range objects, hindering the detection of distant objects.

- **Complex data processing:** in-vehicle computing systems struggle to execute computer-vision safety-based tasks, such as object detection and recognition. The absence of a unified data format further complicates data fusion and processing.

1.2 Research statement

In order to make up for the insufficiency of autonomous driving perception capability and data processing above Level 3, advanced sensing technology, and especially communication need to be combined to build an autonomous driving cooperative perception system, enhancing perception accuracy, and improving the perception range.

The challenge lies in determining which data would be valuable for each vehicle in a given scenario. An illustrative scenario occurs when a vehicle detects an obstacle in close proximity to another vehicle, but the presence of this obstacle remains unnoticed by nearby vehicles due to obstructed lines of sight caused by other obstacles or structures. Alternatively, consider a situation where numerous obstacles surround a vehicle, providing it with a comprehensive understanding of the scene, while other vehicles positioned further away have only limited information about the environment.

For this reason, data dissemination in order to achieve full perception is crucial. However, it is necessary to discriminate the importance of the retrieved data in order to avoid exchange of huge volumes of data that can be can be challenging to handle for standard communication technologies [8].

Cooperative perception refers to the concept of AVs sharing sensor information and data with each other to enhance their collective awareness of the surrounding environment. In essence, it is a collaborative approach where vehicles work together as a networked system to gather, process, and exchange information to build a comprehensive representation of the surrounding environment.

At the heart of cooperative perception there are various communication technologies that enable vehicles to exchange data seamlessly. This includes Vehicle-to-Vehicle (V2V) communication, where vehicles directly communicate with each other, and Vehicle-to-Network (V2N) communication, where vehicles communicate with the network, i.e., a Road Side Unit (RSU), supervising the road environment [9] [6].

- **Vehicle-to-Vehicle (V2V) communication:** V2V communication technology facilitates the exchange of data between vehicles using dedicated short-range communications (DSRC). V2V systems are positioned to have a significant impact on vehicle safety applications, particularly in crash avoidance. V2V enables vehicles to receive information about the speed and position of nearby vehicles, helping to alert drivers of potential dangers and reduce accidents and traffic congestion. This technology can detect hazardous traffic conditions, road terrain issues, and weather threats within a range of 300 meters, thereby enhancing driving predictability and safety.

- **Vehicle-to-Network (V2N) communication:** V2N communication permits the exchange of data to/from the network via legacy cellular technologies. [10]. V2N technology provides real-time notifications to drivers about nearby dangerous weather conditions, accidents, traffic congestion, and other hazards. This information is delivered directly to vehicles, reducing driver reaction time and improving overall safety.

While V2V communication represents the future of autonomous driving, widespread adoption is still in progress, with the technology set to be most effective when implemented across all types of vehicles, including trucks, buses, cars, motorcycles and even bicycles [11].

In this framework, each vehicle is assimilated to a source of information for others, while simultaneously benefiting from the data received from other vehicles. Broadcasting every observation collected by a vehicle would quickly saturate the communication channel, especially in densely populated urban scenarios where the density of vehicles per unit area is particularly high [12]. For this reason, it is important that every AV is capable of processing its onboard sensory data, especially if they provide useful information of potential obstacles in the surrounding, and evaluate whether they may be valuable for potential receivers in the vicinity.

1.3 Thesis Objectives

The main goal of this thesis is to develop a reliable and robust algorithm for gathering and sharing information regarding obstacles detected by AV sensors within a specific context. Our objective is to assess the value of the information collected by each vehicle and determine its relevance for sharing with other AVs in the same scenario. The ultimate goal is to create an efficient system that minimizes the amount of data that are disseminated in the vicinity to allow potential receivers to detect unknown obstacles.

This obviously can be achieved by sharing all the sensory data collected by each vehicle to everyone. However, given the limited bandwidth available, this would be impractical in a real scenario. This strategy however will be our initial benchmark for analyzing the quality and redundancy of exchanged messages. This will help us determine which information is crucial to share and which can be overlooked.

In summary, this thesis seeks to address the challenge of cooperative perception in intelligent vehicle networks by developing an algorithmic solution that promotes efficient information sharing while considering parameters like redundancy and quality of data without sacrificing the system's accuracy.

In order to achieve this goal, we developed a simulator capable of generating scenarios populated with AVs and obstacles, allowing us to evaluate the performance of adopted communication methods. These scenarios were crafted using real-world intersection data obtained from **OpenStreetMap**. This methodology facilitated the testing and validation of data collected from our simulations across various real-world intersections. Specifically, we assessed our algorithms in both urban and rural settings, that is considering different types of traffic congestions on the road, ensuring comprehensive evaluation across diverse environments.

Regarding the images captured by sensors, they constitute a central aspect of our work, as they represents both the source from which AVs' object detection algorithms retrieve the obstacles data and the object shared among all vehicles. In our work, we considered the **SELMA dataset** [13], which includes a a wide array of images and data collected by sensors in diverse traffic scenarios. By making assumptions based on this dataset, we were able to make considerations regarding the obstacles encountered, such as their distance from the sensor and their position in relation to the vehicle direction.

Based on the scenario generated and the information derived, we proceeded to make geometric considerations, with particular emphasis the *Line of Sight (LoS)* of the vehicle and its *Field of View (FoV)*. Specifically, we considered 4 values as useful elements in calculating the importance of the detected data for an obstacle:

- Distance between the sender and the perceived object.
- Distance between the receiver and the perceived object.
- Orientation difference between the sender direction and the perceived object.
- Number of obstacles detected in the image.

Building upon these values, we developed a methodology based on **Analytic Hierarchy Process (AHP)** to calculate the **Value of Information (VoI)** of each image [14].

We developed, implemented, and evaluated the following dissemination algorithms:

- **Broadcast method (benchmark)** Where each vehicle shares all collected images with all other vehicles.
- **Partial broadcast (or naive)** Where a vehicle unaware of an obstacle receives images from other vehicles that have information about that obstacle.
- **Optimized method (proposed)** Where before sending messages, each vehicle assesses how useful the information it possesses could be to every other vehicle. Consequently, message transmission priority is given to the vehicle with the most valuable information.

We compare the different algorithms based on a large and consistent number of iterations and different parameters were modified, Including the position and number of obstacles, the position and number of vehicles, the topology of the in road intersections and AHP parameters. We evaluate the different algorithms performance in terms of the number of exchanged messages, percentage of redundancy and the quality of obstacle data (represented by the distance of the obstacle from the sensor that detected it).

Thanks to our simulations, we have demonstrated that our proposed dissemination algorithm can reduce the number of exchanged messages of by approximately 80% compared to the broadcast method and approximately 45% compared to the partial-broadcast method. While the broadcast method ensures the better obstacle quality, as the AVs HAVE access to all the collected data. Tthe obstacle quality of the optimized methods is excellent, considering the significant gain in terms of exchanged messages. Finally, we also highlighted that through the definition of various sets of values for the AHP method, it is possible to achieve subtle better performance depending on the type of scenario and on the choice of the parameters.

1.4 Organization of Thesis

The contents of this thesis are structured as follows: Chapter 1 provides a general introduction to the topic and outlines the thesis objectives. Chapter 2 consists of a literature review, offering an overview of the context in which we operate and the technologies utilized. Chapter 3 details the structure of the simulator and presents the organization of its classes along with key functionalities. Chapter 4 provides a comprehensive description of the simulation environment, including configuration instructions and key functionalities. Additionally, it presents a case study illustrating the behavior of three types of communication scenarios and the underlying algorithmic insights. Chapter 5 evaluates the performance by simulating various scenarios as a function of different simulator parameters. Finally, Chapter 6 concludes our work, drawing conclusions and suggestions for future work.

Chapter 2

Literature Review

This chapter will provide an overview of various technologies employed in the contexts of interest, such as Vehicular Networks (V-NET) and perception systems, including cameras and Light Detection and Ranging (LiDAR) sensors, as well as V2V communication technologies.

2.1 Connected Autonomous Vehicles CAVs

2.1.1 VANETs

In automotive applications, Cooperative Perception for Connected Vehicles has been extensively studied in the recent years and in the near future, most new vehicles will be equipped with short range radios capable of communicating with other vehicles [15]. The importance and potential impact of V-NET, and more specific in Vehicular AD-hoc Networks (VANETs), have been confirmed by the rapid proliferation of consortia involving car manufactures, various government agencies and accademia. Examples include, among others, the Car-2-Car Communication Consortium, the Vehicular Safety Communication Consortium the Advanced Safety Vehicle Program [16].

At its core, V-NET facilitates the exchange of critical information among vehicles and infrastructure elements in real-time, towards the concept of Connected and Autonomous Vehicles

(CAVs). This communication network encompasses a wide array of technologies, including Dedicated Short-Range Communication (DSRC) [17], Cellular Vehicle-to-Everything (C-V2X) [18], and emerging 5G networks, each offering unique capabilities and applications.

2.1.2 Cooperative Perception

CAVs relies on multiple sensors, LIDARs and radars to detect surrounding objects, but, despite their precision, they also come with limitations. They have limited visibility [19] and may not detect all road agents that are relevant to their operation and a vehicle cannot detect objects occluded by other obstacles.

In [20], an interesting scenario is presented where autonomous vehicles make incorrect decisions due to inaccurate detection and recognition. As described in that analysis, one possible solution for a vehicle to address this issue is by combining its own data with that of other vehicles. By integrating incoming information from different perspectives, the vehicle can increase its awareness of the environment, thus enhancing road safety.

The typical information exchanged among vehicles in cooperative perception includes vehicle states, encompassing position, velocity, acceleration, and orientation [7]. However, other studies explore alternative data types, such as raw sensor data [20], image features [21], or propose innovative routing protocols for cooperative perception [22]. The choice of information shared depends on the intended application of cooperative perception. For instance, raw sensor data or a combination of raw and processed data are shared to enhance object detection, while novel routing protocols aim to optimize information relevance in the network and reduce redundant data to enhance network capacity [23].

In [20], to enhance object detection in three-dimensional space, an effective strategy is to transmit point clouds data and by fusing raw sensor information, where input data are collected from various perspective before object detection is performed. This approach mitigates the limitations of single line-of-sight observations. LiDAR or RADAR sensors are typically preferred for this purpose, as they inherently provide point clouds, which are more straightforward to integrate.

2.1.3 Object detection models

Extensive research has been conducted in the literature. We briefly summarize the main object detection baselines for both the cameras-images and point cloud inputs. For image-based object detection, Convolutional Neural Networks (CNNs) are extensively utilized. Prominent models in this domain include the Single Shot MultiBox Detector (SSD) [24], You Only Look Once (YOLO) [25], and RetinaNet [26], which are capable of real-time object detection and classification. On the other hand, point cloud-based detection often employs algorithms like Pixel-Wise Detection Network for Autonomous Driving (PIXOR) [27], Sparsely Embedded Convolutional Detection (SECOND) [28], and PointPillars [29]. These models directly process 3D point cloud data and exhibit real-time object detection capabilities in the surroundings of Autonomous Vehicles (AVs).

In our research, we prioritize the value of information in relation to information content for specific receivers and the utilization of communication resources. Consequently, we do not focus on any particular sensor or object detector. Instead, we simulate the local perception system by utilizing the geometric structures of the roads and vehicles.

2.2 Unicast Transmission and Millimeter Wave Communication

Cooperation Perception is a message sharing system for sensed information in the surrounding environment. Essentially, there are two different ways to share this information, and each method has different requirements. The first one is unicast in which communications occurs for pairs of sender and receiver. The second approach is broadcasting in which communications happens when a sender shares information with all the nearby receivers. In this section we are going to discusses the former .

The unicast approach requires an association of two connected vehicles such that one vehicle (the sender) sends a message to the other vehicle (the receiver). Moreover, the sender has to select the information that is relevant to the receiver. This is done through a scoring function that calculates how important the information is to the receiver. Additionally, unicast has the advantage to optimize one or more of the network resources. For instance, the selection of the resource blocks or the transmission power can be made to optimize the communication given the locations of the sender and receiver.

The unicast approach is ideal for our research, and we have chosen this method to leverage millimeter-wave (mmWave) communication. This technique involves utilizing mmWave frequencies, which refer to radio frequencies in the range of 10 GHz to 300 GHz, for wireless communication [17].

The benefits that this type of technology offers in the context of CAVs are discussed in [12]. Firstly, it provides high data rates, crucial for transmitting large amounts of data in real-time. Secondly, mmWave communication offers low latency due to the high frequency and short wavelength of mmWave signals, enabling quick signal propagation. This low latency is essential for applications like V2V communication, where real-time response is critical for safety. Moreover, mmWave frequencies provide a large bandwidth, allowing for the transmission of large amounts of data simultaneously [30]. This is beneficial for supporting multiple communication streams in dense automotive environments. This type of communication systems can utilize beamforming techniques to focus the signal towards specific receivers, increasing signal strength and reducing interference. This is particularly advantageous in environments with high mobility and varying signal conditions, such as urban or highway scenarios. By adopting the unicast approach with mmWave communication, we can ensure efficient and reliable communication between connected vehicles. The sender can select relevant information and transmit it to the receiver using optimized network resources. This approach maximizes the benefits of mmWave communication in the automotive domain, enabling high-speed, low-latency, and reliable communication.

2.3 Information Relevance

While the prospects mmWaves are promising and lend themselves as valuable assets in the world of CAV, the scientific community argues that even a substantial increase in channel capacity may not be adequate to meet the most ambitious Quality of Service (QoS) requirements of future automotive applications. This is especially true in scenarios with multiple active services that demand varying degrees of automation [12].

Addressing the challenges posed by a vast amount of information, particularly in dense road traffic scenarios, entails mitigating redundancy and irrelevancy, as well as consumptions of network resources. Redundancy occurs when receivers receive identical information from different or the same senders, while irrelevancy arises when receivers receive information not pertinent to them.

Various approaches in the literature model information importance, often influenced by the type of information used. One common approach involves taking in consideration the region of interest ROI around connected and CAVs and assessing information importance based on its relevance to the receiver [31]. Other methods include trajectory-based information calculation and leveraging object-to-receiver visibility [32]. The advantage of using trajectory-based information calculation is that it allows working on specific objects rather than the sparser ROI structure. Moreover, it leverages the safety feature, where the information importance is directly tied to potential collisions and accidents. Empowered with the information importance score function, the authors of [57] design a distributed scheduling broadcasting for a scalable cooperative object detection.

In our research, we have chosen a different approach that involves the utilization of the AHP to calculate an importance value that takes into account various factors, such as the number of detected obstacles, the distance from the sensor, and the consideration of ROIs of other AVs [23]. The implementation details of this technique will be thoroughly discussed later on, but through this methodology, we were able to define functions that model these aforementioned parameters. Furthermore, it enabled us to determine the importance of each element relative to others.

The incorporation of the AHP into our framework offers several advantages. Firstly, it provides a systematic and structured approach to decision-making, allowing us to consider multiple criteria and their relative importance. This is particularly valuable in the context of cooperative perception, where various factors contribute to the overall perception quality. By assigning weights to different criteria based on their significance, we can effectively prioritize information sharing and optimize resource allocation.

Moreover, the flexibility of AHP allows for the adaptation of the model to different scenarios and environments. This versatility enables us to tailor our approach to specific use cases, ensuring its applicability across diverse settings. Additionally, the transparency and comprehensibility of the AHP facilitate clear communication and understanding of the decision-making process, both within the research community and among stakeholders.

Furthermore, the use of AHP promotes consistency and repeatability in our evaluations. By establishing a standardized framework for assessing the importance of information, we can ensure reproducibility across experiments and comparisons between different methodologies. This enhances the reliability and validity of our findings, contributing to the robustness of our research outcomes.

Chapter 3

Simulator

In this work we have developed a Python simulator to serve as a test bench for generating various scenarios of interest and evaluating the performance of our data dissemination algorithm. This chapter will introduce this simulator along with the implementation details.

In this chapter, we will present the main actors to our context and present the UML class diagram of our simulator, identifying the key entities and outlining their attributes and relationships.

3.1 Description of the simulator structure

The simulator consists of several key components designed to simulate autonomous vehicle behavior, perception, and communication within a controlled environment and considering factors such as communication range, obstacle detection, and cooperative perception.

Moreover, users can dynamically position AVs anywhere in the simulated environment, facilitating the exploration of various spatial configurations. This capability is crucial for evaluating the system's performance under different conditions and adjusting parameters to reflect real-world challenges.

Furthermore, the simulator allows users to customize the number of AVs and the number of obstacles in the simulation, offering insights into the scalability of the AV system under varying conditions. This flexibility enables the exploration of scenarios with dense traffic, where bandwidth resources are limited, and prioritization of the most useful information is necessary.

Now, let's delve into the practical implementation details of this simulator. The simulator's implementation in Python leverages the object-oriented paradigm, allowing for the creation of modular and reusable components. Here's an overview of the key aspects of its implementation:

- **Object-Oriented Approach:** The simulator is designed using object-oriented principles, where each entity is represented as an object with its own attributes and functions.
- **Actor Identification:** The first step in the implementation process involved identifying the primary actors that interact within the simulated environment. These actors include autonomous vehicles, obstacles, and the map layout.
- **Scenario Generation:** : With the actors identified, the simulator generates scenarios by populating the map with intersections and configuring the initial positions and characteristics of AVs and obstacles. These scenarios serve as the basis for conducting simulations and evaluating algorithm performance.
- **Communication Simulation:** Communication among autonomous vehicles is a critical aspect of the simulator's implementation. This functionality enables AVs to exchange perception data, coordinate their actions, and enhance overall traffic awareness. The communication simulation involves three types of communication: including *broadcast communication*, *partial broadcast communication* and *optimize communication*, which we will analyze in the following sections.

We now introduce the outline the principal entities of this simulator.

- *Autonomous Vehicle (AV)*
- *Obstacle*

- *Map*

3.1.1 Autonomous Vehicle (AV)

Let's delve into the role of the Autonomous Vehicle (AV), which is the primary actor in our case study and constitutes the core element of CAVs. Here, we have made some assumptions based on the considerations outlined in Chapter 2. These assumptions serve as the foundation upon which we have built our framework, with the aim of focusing on our objective.

Communication Capabilities

At the heart of our examined network lies the AV with its communication capabilities, around which CAVs revolve. In our work we assumed that AVs utilize mmWave technology for communication in short range scenario [12], facilitating efficient data exchange. Through this technology, the vehicles engage in communication via V2V, sharing information on the status of the vehicle.

Object Detection Capabilities

The vehicle is equipped with computational capabilities enabling the application of object detection algorithms. These algorithms aim to distinguish between static environmental elements and dynamic obstacles, such as pedestrians and moving vehicles, which are the focus of our study. This computational capability allows the vehicle to analyze sensor data in real-time, accurately identifying and categorizing objects based on their characteristics.

Sensor Capabilities

The AV's sensor suite plays a fundamental role in its perception processes. In the literature, numerous studies, such as SELMA [13], underscore the pivotal role of sensor technology in autonomous driving systems. These sensors are strategically mounted on the vehicle, leveraging their diverse functionalities to capture a comprehensive view of the environment. The integration of sensors on autonomous vehicles is designed to maximize coverage and efficacy in detecting and interpreting environmental elements.For instance, LiDAR sensors provide precise distance measurements by emitting laser pulses and measuring their reflections on surrounding objects. In our work, we consider AVs equipped with four cameras, one for each direction, to capture images, along with LiDAR sensors to gather information about the distance from objects.

Figure 3.1 illustrates the arrangement of cameras and sensors mounted on autonomous vehicles for generating the Selma dataset [13].

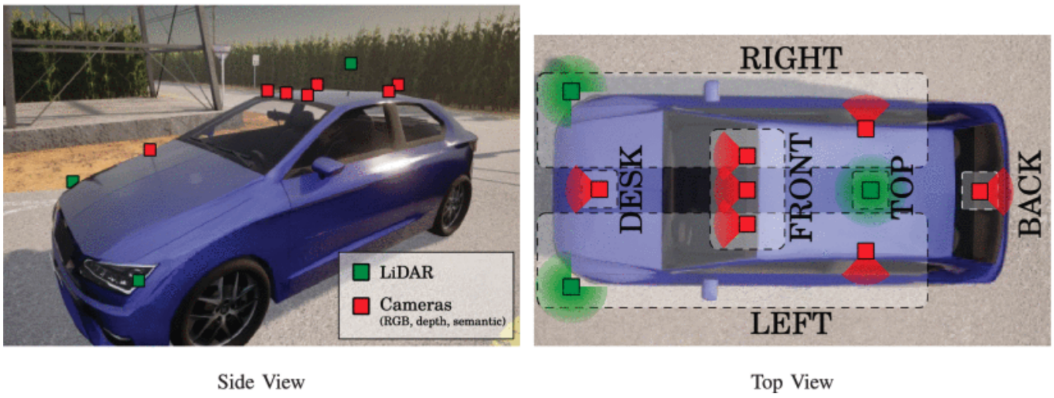


Figure 3.1: Sensors positioning on the simulation car in the process of generating the SELMA dataset in [13]

Information Fusion

An essential aspect of the AV's functionality is the integration and fusion of sensor data to form a coherent representation of its surroundings. Through sophisticated algorithms [20], the AV combines data from multiple sensors, such as LiDAR point clouds and camera images, to generate a rich and accurate perception of the environment and to mitigate the limitations of single line-of-sight observations by fusing raw sensor information

In our work, this capability allows us to share point cloud data among the various AVs and to mitigate the limitations of single line-of-sight observations by fusing raw sensor information.

This enables us to reconstruct and recognize obstacles in the surrounding environment.

This process of information fusion allows the AV to effectively identify and track obstacles, predict their future movements, and make informed decisions based on the perceived environment.

3.1.2 Obstacle

The Obstacle is a fundamental component of our simulation framework, representing entities within the environment that pose potential hazards to autonomous vehicles. These obstacles can be assimilated as a wide range of objects, both static and dynamic. One of the primary objectives of our research is to facilitate detection of obstacles in the surrounding environment to promote, emphasizing collision avoidance.

Integration with Cooperative Perception Algorithms

Within the simulation framework, cooperative perception algorithms implemented within autonomous vehicles closely interface with obstacle data. These algorithms process incoming obstacle data from neighboring vehicles, incorporate it into the vehicle's perception model, and contribute to collective situational awareness. By integrating obstacle information from multiple sources, CAVs can build a more comprehensive and accurate representation of the environment, enhancing overall traffic safety and efficiency.

3.1.3 Map

In our work, the Map assumes a central role, dictating the layout of roads, intersections, and obstacles that populate the landscape. It is within this digital realm that the dynamics of traffic awareness, collision avoidance, and cooperative behavior among AVs are explored and analyzed. It embodies all the features that will determine which and what type of information will be shared within the network. It is where the simulation takes place and where the other actors must operate.

Open Street Map

One crucial aspect of our implementation is the utilization of *OpenStreetMap (OSM)* data as the basis for scenario generation. OpenStreetMap provides a rich, open-access database of real-world geographic data, including detailed road networks, intersections, and other relevant features. By leveraging OSM data, we ensure that our simulated environments closely resemble real-world road networks, enhancing the authenticity and applicability of our simulations.

The primary advantage of using OSM data lies in its richness and accuracy. OSM data is crowdsourced and continuously updated by contributors worldwide, resulting in highly detailed and up-to-date representations of road networks. This granularity allows us to simulate complex traffic scenarios with a high degree of fidelity, including various road types, traffic regulations, and infrastructure features.

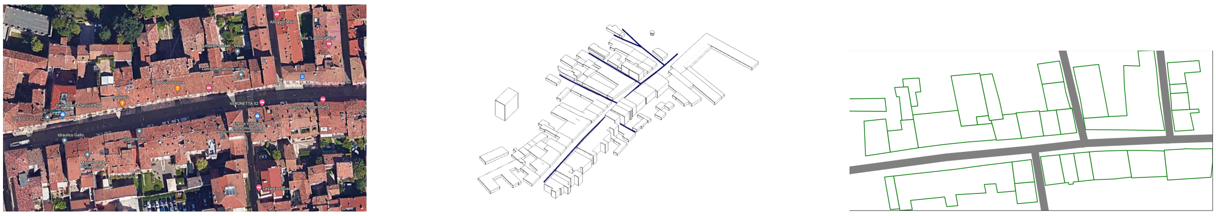
In our implementation, we utilize GeoJSON files derived from OpenStreetMap data to represent road networks and other geographic features. By leveraging GeoJSON files, we can easily parse and integrate OSM data into our simulator, streamlining the process of scenario generation and ensuring consistency with real-world geography.

By extracting the geometric properties the data, we were able to delineate the structural characteristics of the simulated environment with precision and accuracy. These geometric properties serve as foundational elements for our analysis, enabling the definition of critical parameters such as:

- Line of Sight: Utilizing the geometric properties extracted from the files, we conducted analyses to determine the line of sight for intelligent vehicles within the simulated environment. This involved assessing visibility constraints imposed by buildings, terrain features, and other obstacles to ensure realistic perception capabilities for the vehicles.

- Regions of Interest: utilizing the geometric properties, we defined Regions of Interest (ROIs) for Autonomous Vehicles (AVs) to prioritize areas along their direction of travel. By analyzing geometric properties from geojson files, we identified ROIs emphasizing regions ahead of AVs rather than those behind. This ensures AVs focus on information relevant to their immediate and future trajectory, enhancing efficiency and safety in dynamic environments.

In Figure 3.2 an example of an actual intersection where we can observe the satellite image, the 3D reconstruction of buildings, and their geometric properties extracted from our simulator.



(a) Satellite Image (b) 3D Reconstruction (c) Simulator

Figure 3.2: Example of intersection

3.2 UML and Implementation of Key Functionalities

Now that we have identified and discussed the features of the most important actors, let's now present the UML diagram of our simulator. The UML diagram is used to visually represent the classes, attributes, functionalities, and relationships within our system.

The main classes of the UML diagram are desribed below.

- *Autonomous_vehicle*

  The *Autonomous_vehicle* class represents individual AVs within the simulation. Each AV object possesses attributes such as ID, latitude, longitude, and orientation, which define its position and heading. Additionally, attributes like *AVs_in_range* and *obs_detected* store information about neighboring AVs and detected obstacles, respectively. These attributes are crucial for the AV's perception and decision-making processes. The functions within the *Autonomous_vehicle* class facilitate the retrieval of detected obstacles (via *get_obs_detected()* method) and determination of their relative direction (via *get_direction_obs(obs) method*). These functions enable the AV to gather relevant perception

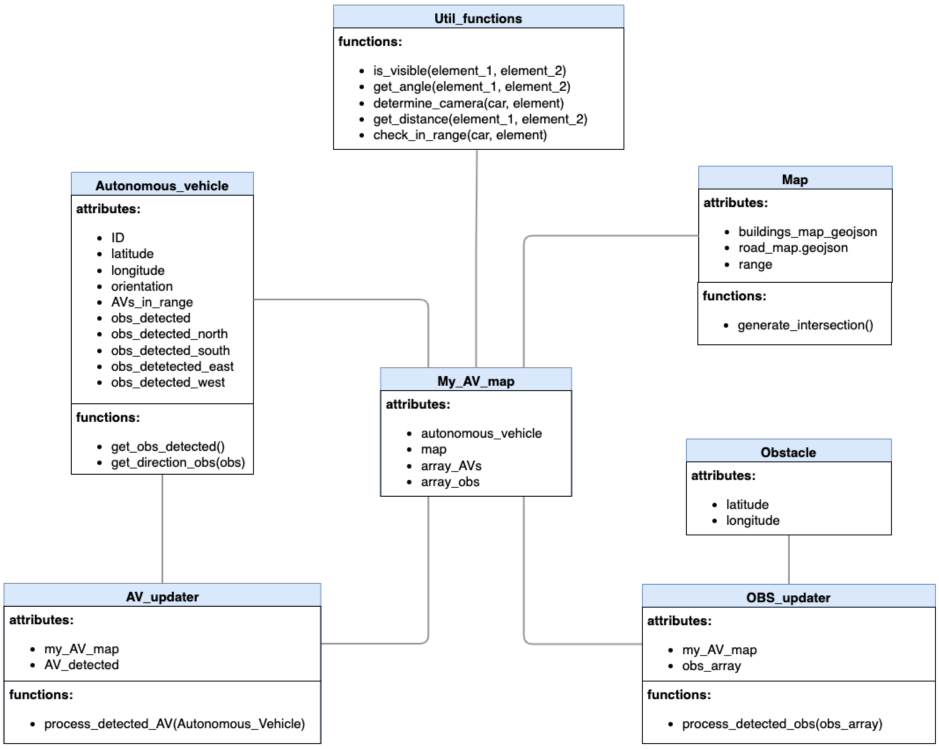


Figure 3.3: UML schema of the simulator

data from its surroundings, both of which are essential inputs of our data dissemination algorithms.

- *Map*

  The *Map* class represents the environment in which the simulation takes place. It includes attributes such as *buildings_map_geojson* and *road_map_geojson*, which contain geographical data defining the layout of buildings and roads. The *range* attribute specifies the size of the map.

- *My_AV_map*

  The *My_AV_map* class serves as a container for managing AVs and their interactions with the map environment. It includes attributes like *autonomous_vehicle* (representing the AV objects), *map* (representing the map object), *array_AVs*, and *array_obs* (storing information about detected obstacles). This class facilitates the coordination and integration of AVs within the simulated environment.

- *AV_updater*

  The *AV_updater* class is responsible for updating information about detected AVs within the simulation. It interacts with the *My_AV_map* object to process detected AVs and update relevant data. The *process_detected_AV()* function handles the updating process, ensuring that the simulation accurately reflects the presence and movements of neighboring AVs.

- *OBS_updater*

  Similarly, the *OBS_updater* class updates information about detected obstacles within the simulation. It interacts with the *My_AV_map* object and receives input from an *obs_array* containing information about detected obstacles. The *process_detected_obs()* function manages the updating process, ensuring that the simulation accounts for obstacles in the environment.

- *Util_functions*

  The *Util_functions* class provides a collection of utility functions essential for various aspects of the simulation. These functions include *is_visible()*, *get_angle()*, *determine_camera()*, *get_distance()*, and *check_in_range()*. They facilitate calculations related to visibility, orientation, distance and range, crucial for perception and decision-making processes within the simulation.

3.2.1 Data Dissemination

Based on the presented classes, our simulator will generate scenarios where vehicles and obstacles are present in the intersections. The next chapter will introduce three data dissemination algorithms that implement different strategies for message generation by vehicles. Through these considerations, the messages exchanged between vehicles will vary significantly. We will then evaluate the results using a Monte Carlo approach to assess the performance of the various strategies.

Chapter 4

Data Dissemination Algorithms

In this chapter, we will introduce and explain three strategies for disseminating sensory data in the network: Broadcast Communication , which will serve as our benchmark; Partial Broadcast Communication , a more elaborate algorithm but not yet optimal; and finally, Optimized Communication , which, with the introduction and analysis of the Value of Information concept, will represent our optimized algorithm.

First, in Sec. 4.1 we present our scenario configuration. Then, in Sec. 4.2 we describe our data dissemination algorithms.

4.1 Configure Simulation Environment

In this section, we describe our simulation scenario, their positions (latitude and longitude) in the environment, and the orientations (in degrees) of the directions in which the vehicles are moving. An example of a possible scenario configuration for the vehicles is reported in Table 4.1.

Similarly, we then define a number of obstacles and their positions. An example of a possible scenario configuration for the obstacles is reported in Table 4.1.

ID	Latitude	Longitude	Orientation
A	11.007767285707814	45.439492436628484	92
B	11.007789421555742	45.43937903284822	91
C	11.007903263242582	45.439586043947855	183
D	11.007484262837124	45.43954676351245	0
E	11.008225211533869	45.43960992760452	180
F	11.007983298078727	45.439737059970014	271

Table 4.1: Example of car data of a possible scenario

Object ID	Longitude	Latitude
obs01	11.007994965432141	45.43956251307974
obs02	11.007259879567288	45.439501301102375
obs03	11.007524314620381	45.43957334519733
obs04	11.00811932397948	45.43955290255859
obs05	11.007794071474587	45.43945523711499
obs06	11.008327864869	45.43958895589447
obs07	11.007239494837371	45.43954782572268
obs08	11.007182339769145	45.439518758415836
obs09	11.007204585265388	45.43954086015715

Table 4.2: Example of obsyacle data of a possible scenario

1. Map Generation

The simulation setup begins with the generation of the map, which is accomplished by defining polygons representing the geometry of buildings extracted from the files. These polygons serve as the spatial layout of the simulated environment, providing the infrastructure for AV navigation and obstacle placement.

2. Vehicle Deployment

Next, the AVs are deployed onto the map where they are ready to navigate through the simulated traffic scenarios.

3. Obstacle Deployment

Obstacles are deployed onto the map based on predefined data. By strategically placing obstacles within the simulation, we create realistic scenarios that challenge the AVs' perception and decision-making capabilities.

A representation of a possible scenario configuration is depicted in Fig. 4.1. The Figure 4.1 represents a potential scenario of our simulator. It should be noted that this representation is a case study with fixed parameters. The results presented in the next sections will be derived from a large number of simulations conducted with varying parameters.

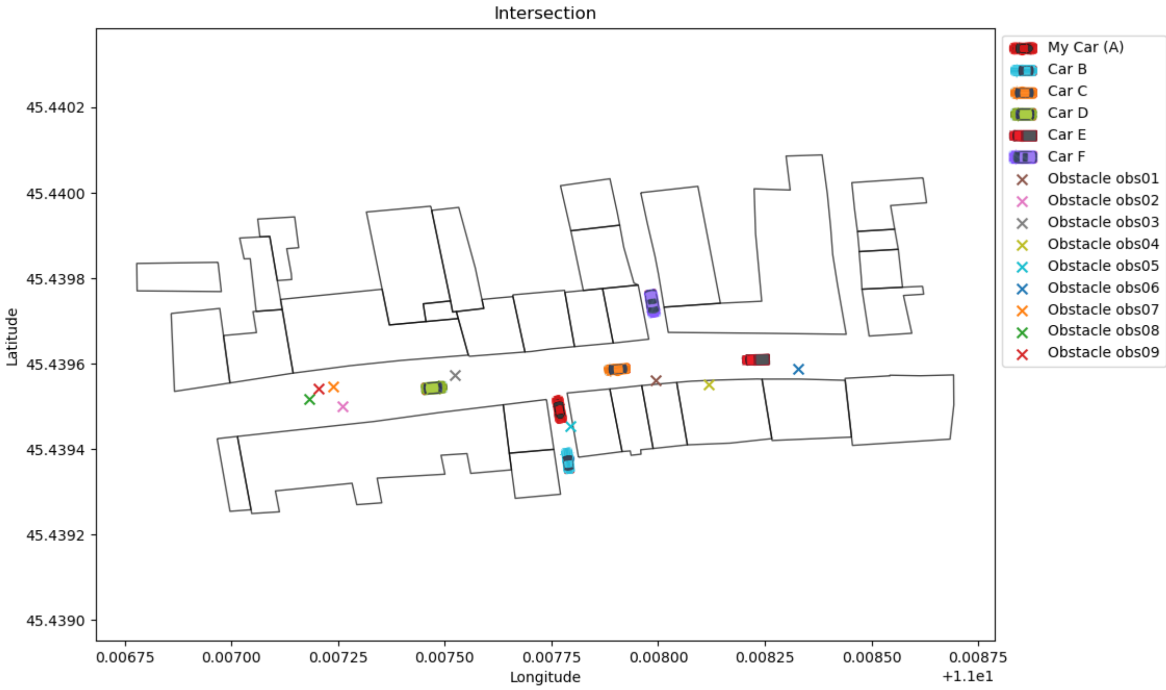


Figure 4.1: Case study

4.2 Data dissemination algorithms

Now that we have examined how our scenario, populated with our actors, is generated, let's proceed to explore the classes of the implemented data dissemination algorithms. The purpose of these algorithms is to share information collected by the vehicles' sensors with other vehicles in the CAV. Depending on the strategy implemented in each context, each vehicle make decisions based on the information it has collected. According to these considerations, each vehicle will decide whether to send messages and to whom. The three types of algorithms that we will present in the next sections (Broadcast Dissemination, Semi-Broadcast Dissemination and Optimized Dissemination) represent the strategy that each vehicle employs, based on the data it possesses, for message generation and receiver selection. During the simulation, each vehicle will generate a series of messages, each intended for a specific receiver determined by the specific situation. In our work, we make assumption that vehicles are aware of the positions of other intelligent vehicles and can fairly accurately predict which obstacles other vehicles are aware of. This will be accomplished relying on the ETSI protocol [33], which assumes a continuous exchange of such information. In order to evaluate the overall performance of the network, our simulator will keep track of all generated messages to assess the performance of the various strategies. In Figure 4.2, we present the classes developed for each category of dissemination strategies and we evaluate the following metrics:

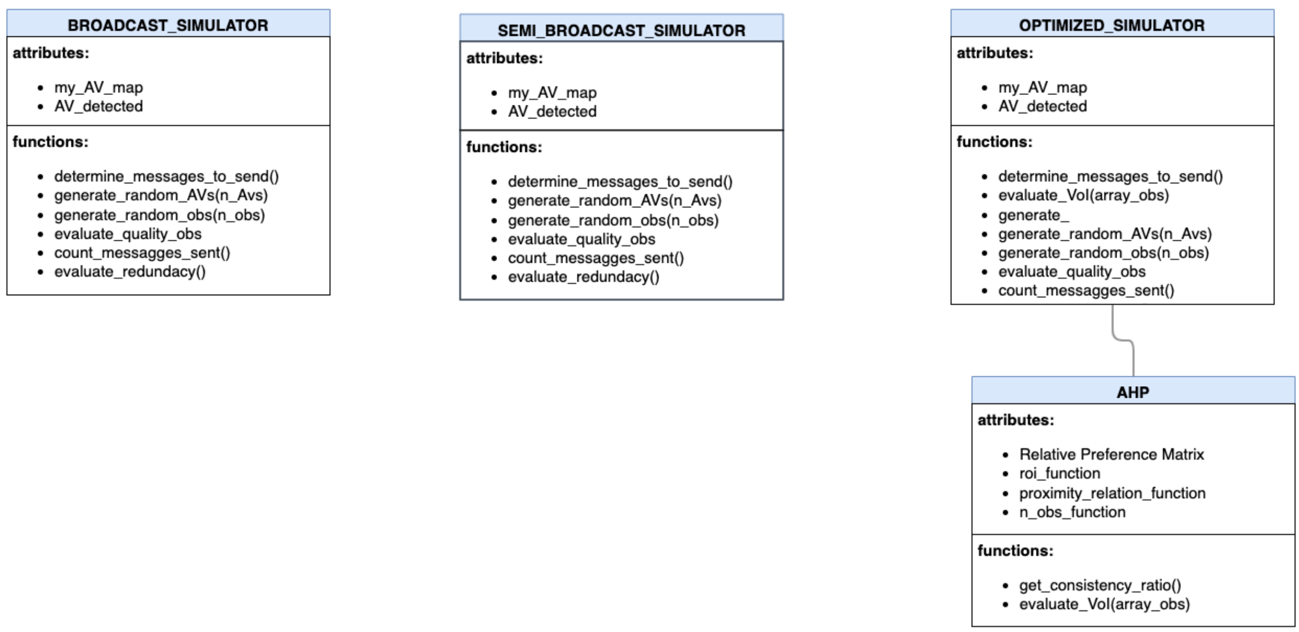


Figure 4.2: Simulation classes

- **Total messages sent**

  To assess the performance of communication among AVs within a CAV aimed at sharing information about all obstacles, we begin by considering the total number of messages exchanged between vehicles. This metric represents the sum of all messages sent by each vehicle within the system. By quantifying the volume of communication, we gain insights into the intensity of information exchange and the overall network activity.

- **Redundancy**

  A fundamental metric in our study is redundancy, which reflects the extent of unnecessary message duplication within the communication network. While achieving our objective of disseminating obstacle information to all vehicles is straightforward without bandwidth constraints, an indiscriminate approach of relaying all gathered information to every vehicle would result in excessive redundancy. Factors such as bandwidth limitations, temporal relevance of information, and the efficiency of message transmission necessitate minimizing redundancy. In our analysis, a message is deemed redundant if the receiver already possesses knowledge of the data it receives.

- **Average distance**

  Average distance serves as a metric to measure the quality of shared information within the network. Specifically, for a visible obstacle, it represents the average distance of the obstacle from the sensor that detected it. This metric provides valuable insight into the relevance and usefulness of the information shared among vehicles. Due to sensor resolution, the closer an object is from the sensor that detected it, the higher the quality of the information obtained.

In the following sections we describe our data dissemination algorithms illustrating how they work and presenting the results obtained for a case study. The information that the presented results are obtained using the Monte Carlo method and through a large number of simulations. The analysis was conducted using a stochastic simulation technique involving the generation of multiple random scenarios to assess the system's performance under various conditions and provide a probabilistic estimate of the results.

4.2.1 Broadcast Dissemination

Now, we will introduce the broadcast method, which serves as the benchmark for our analysis. The strategy behind this approach is relatively straightforward, as it involves sharing all information from all vehicles with every other vehicle in the network. In the context of static capture, where each vehicle captures an image in every direction, the total number of messages exchanged remains constant. This can be calculated using the formula:

$$n_{\text{messages\_sent}} = n_{\text{vehicles}} \times (n_{\text{vehicles}} - 1) \times 4 \tag{4.1}$$

This formula represents the total number of messages sent, where n_{vehicles} denotes the number of vehicles in the network. Each vehicle sends information to every other vehicle, excluding itself, resulting in $n_{\text{vehicles}} - 1$ message exchanges per vehicle. Additionally, considering that AVs are equipped with four cameras, one for each one of the four directions (north, south, east, west), the total number of messages sent per vehicle is multiplied by 4.

Regarding the other metrics, we anticipate a high quality of obstacle data, as all vehicles have access to the best available information for every obstacle. Since no optimization is performed in terms of message selection or transmission, we also expect to observe a high redundancy value. This is due to the fact that each vehicle receives redundant information about obstacles that it may already be aware of, resulting in inefficient utilization of network resources.

Fig. 4.3 represents the total number of messages sent and received for each vehicle, where redundancy is highlighted, while the average dissemination results are reported in Table 4.3.

We can observe that:

Metric	Average distance
Total messages	120
Average distance [m]	17.54
Redundancy count	106
Redundancy	88.33%

Table 4.3: Broadcast Simulation

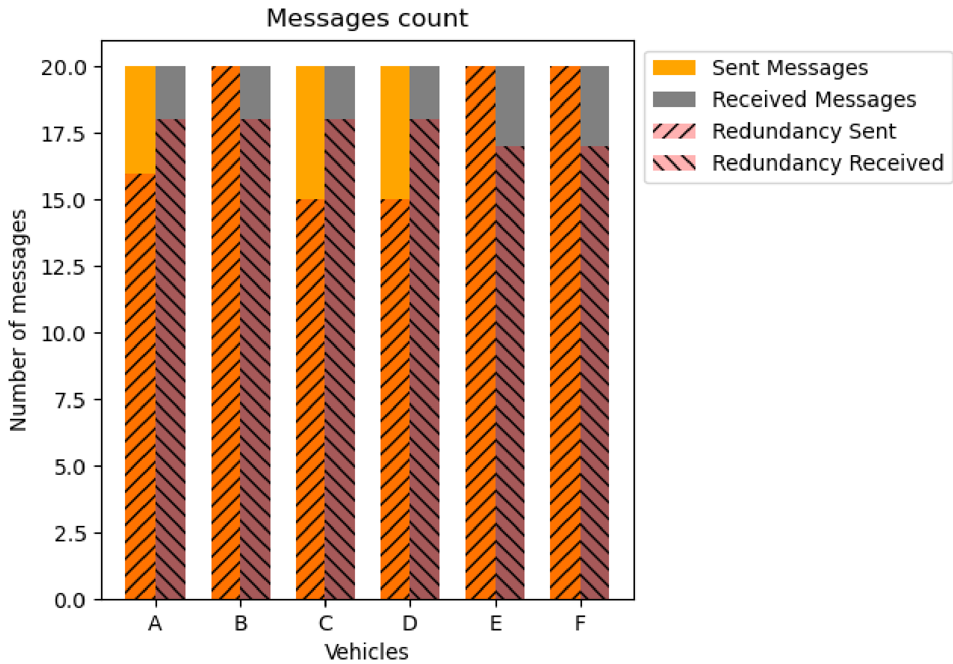


Figure 4.3: Count messages Broadcast

- The total number of messages, at 120, matches our anticipated value calculated using the established formula. This consistency confirms the expected behavior of each vehicle transmitting its captured image to every other vehicle in the network.

- The average distance , measured at 17.54, suggests a satisfactory quality of shared obstacle information. This indicates that, on average, the distance of obstacles from the detecting sensors is notably small, implying accurate data transmission.

- However, the redundancy count of 106 and redundancy rate of 88.33% highlight a significant redundancy in message transmission. As anticipated, the lack of optimization techniques in the broadcast method leads to a large proportion of redundant messages, resulting in communication inefficiencies.

In summary, our results confirm high redundancy in message transmission inherent in the broadcast method. These findings emphasize the importance of implementing optimization strategies to enhance the efficiency of information exchange in cooperative autonomous vehicle networks.

The broadcast method, while simple in its approach, provides a baseline for evaluating the performance of more sophisticated communication strategies. By disseminating all information to every vehicle in the network, it ensures that each vehicle has access to the complete set of data collected by all other vehicles. However, this approach may lead to high redundancy and increased message overhead, particularly in scenarios with a large number of vehicles.

4.2.2 Semi-Broadcast Dissemination (or Naive Dissemination)

Now, we'll present the semi-broadcast or Naive method, which represents a more sophisticated approach compared to the broadcast method. In this method, messages are not sent indiscriminately to all vehicles, but rather based on considerations involving the obstacle information of the sending and receiving vehicles. The semi-broadcast method introduces a level of intelligence into the message transmission process. Instead of blindly broadcasting all information to every vehicle in the network, messages are selectively transmitted based on the relevance of the obstacle information to both the sending and receiving vehicles. Therefore, if there exists an obstacle of which the sender is aware but other vehicles are not, the sender will transmit the sensory data containing this obstacle to all such vehicles. By doing so, no assumptions are made regarding whether other vehicles possess better information than the sender.

With the semi-broadcast or Naive method, the expectation is to achieve a reduction in the total number of exchanged messages across the network. This reduction is achieved by transmitting images containing obstacles only to vehicles that are not already aware of those obstacles. By adopting this strategy, redundant transmissions is reduced. However, this optimization comes at a cost—the sacrifice of the quality of observed obstacles. In this approach, vehicles may not always have access to the most accurate or up-to-date information about obstacles in the environment. Therefore, while the semi-broadcast method effectively reduces network traffic, it introduces trade-offs in terms of data quality. Fig. 4.4 represents the total number of messages sent and received for each vehicle, where redundancy is highlighted, while the average dissemination results are reported in Table 4.4. We observe that:

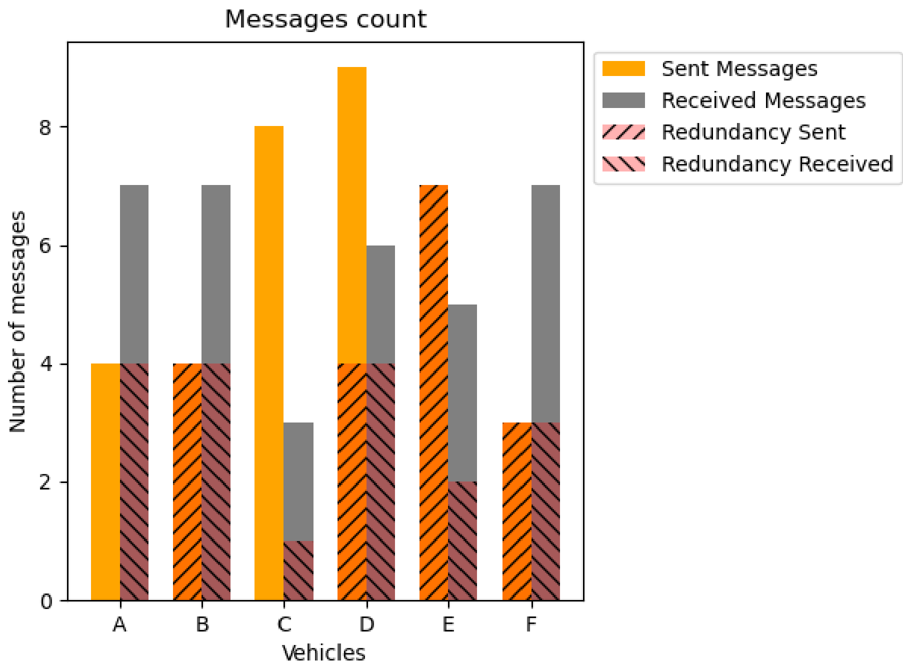


Figure 4.4: Count messages Naive

- The total number of messages sent, which is 35, corresponds to the traffic in the network. With this approach, we can observe a significant reduction in the number of exchanged messages compared to the broadcast method. Notably, the number of messages sent by each vehicle is no longer constant but varies based on the situation.

- The average distance, calculated at 26.73, indicates the quality of the obstacle information exchanged among vehicles. With regard to this value, we can observe a higher average distance compared to the broadcast case, since in this case not all vehicles consistently have access to the best data collected within the network.

- Regarding redundancy, the table reports a redundancy count of 18 and a redundancy percentage of 51.43%. These values, although representing a reduction compared to the broadcast method, still demonstrate a significant degree of redundancy in message transmission.

Metric	Average distance
Total messages	35
Average distance [m]	22.42
Redundancy count	18
Redundancy	51.43%

Table 4.4: Semi-Broadcast Simulation

In summary, the values presented in the table for the Naive simulation are in line with our expectations, indicating a trade-off for optimizing communication efficiency while maintaining the quality of shared obstacle information within the CAV network.

4.2.3 Optimized Dissemination

Let's now introduce the most sophisticated dissemination technique in our project. Keeping in mind the objective of disseminating obstacle information to vehicles within a CAV network, the idea behind this approach is to assess the quality and value of information regarding a given obstacle relative to various receivers. This approach aims to rank the sensory data under many metrics. This ranking process involves estimating the value of information. Expanding on the theory of Analytic Hierarchy Process (AHP), we establish a prioritization framework to determine the significance of each image in terms of its informational value. This framework considers factors such as the proximity of vehicles to the obstacle, the quality of the captured image, and the relevance of the obstacle to each receiver. By applying the principles of AHP, we derive a hierarchical structure to systematically evaluate and rank the images based on their perceived value of information. Building upon this ranking, let's assume we utilize the ETSI protocol for message exchange and we suggest to include the image score in the CPM message, in line with the suggestion in [23], which represents the importance of the image to the receivers.

4.2.4 Value of Information (VoI)

The concepts of VoI in vehicular communications have already been studied in the literature [14] [34]. Specifically, starting from the AHP theory in [14], we define the attributes to assess the VoI in vehicular networks. Then, we assign weights to the different attributes, to indicate how valuable each attribute is compared to the others. Finally, we evaluate how each attribute impact the overall value of information.

Obstacle Attributes

Let's define the attributes that we will consider to assign an importance value to the detected obstacles:

- **Distance between the sender and the perceived object** This attribute represents the distance between the position of the detected obstacle and the position of the vehicle that detected it. The formula for calculating this distance is:

$$D_{\text{sender}} = \sqrt{(x_{\text{sender}} - x_{\text{object}})^2 + (y_{\text{sender}} - y_{\text{object}})^2} \tag{4.2}$$

- **Distance between the receiver and the perceived object** This attribute represents the distance between the position of the detected obstacle and the position of the receiving vehicle. The formula for calculating this distance is similar to the one above

$$D_{\text{receiver}} = \sqrt{(x_{\text{receiver}} - x_{\text{object}})^2 + (y_{\text{receiver}} - y_{\text{object}})^2} \tag{4.3}$$

- **Orientation difference between the sender's direction and the perceived object** This attribute represents the angular difference between the direction in which the sender vehicle is heading and the position of the perceived obstacle. This attribute provides insight into the relative alignment between the vehicle's trajectory and the position of the obstacle. The formula for calculating this difference can be expressed as:

$$\theta = \arctan\left(\frac{y_{\text{obstacle}} - y_{\text{receiver}}}{x_{\text{obstacle}} - x_{\text{receiver}}}\right) - \theta_{\text{orientation}} \tag{4.4}$$

where $\theta_{\text{orientation}}$ represents the direction towards which the receiver is heading.

Image Attributes

Now that we have defined all the relevant attributes for an obstacle, let's also introduce the attribute **n_obstacles**, which refers to the number of obstacles detected within an image. When an AV captures an image of its surroundings, the this attribute provides valuable contextual information about the density of obstacles within the scene. This metric enables us to evaluate the overall importance of a captured image for a potential receiver.

Attribute Priority Weights

First we have to establish the relative priority among obstacle attributes. This is achieved by constructing a *pairwise comparison matrix* with comparison scores. The comparison scores that we can see in Table 4.5 is populated with with comparison scores (ranging from 1/9 to 9) assigned according to the Saaty comparison scale [35] and assess the importance of the attributes in the row relative to those in the column.

	θ	D_{sender}	D_{receiver}
θ	1	α	β
D_{sender}	$1/\alpha$	1	γ
D_{receiver}	$1/\beta$	$1/\gamma$	1

Table 4.5: pairwise comparison matrix

Once the matrix has been defined we calculate the *priority weights* w_a, $a = 1, \ldots, n$, where n is the size of M, that indicate how valuable each attribute is compared to the others. Inorder to do it we evaluate the normalized principal eigenvector $\mathbf{w}^T = \langle w_1, \ldots, w_n \rangle$ of M, i.e., the eigenvector that corresponds to the eigenvalue λ_{max} with the largest magnitude:

$$M\mathbf{w}^T = \lambda_{\text{max}}\mathbf{w}^T \tag{4.5}$$

Conditional VoI

Now we have to evaluate how each defined attribute impacts the VoI score. Let's define the VoI functions.

a) Proximity relation strength function

   For the proximity relation strength attribute we propose a logistic function. This function is utilized for both attributes; where $f_1(\cdot)$ represents the *distance between the sender and the perceived object* and $f_2(\cdot)$ represents *distance between the receiver and the perceived object* since it models the interest an obstacle holds concerning its distance from the vehicle. The proximity relation strength function can be expressed as:

$$f_{1,2}(x, d_0, k) = 1 - \frac{1}{1 + e^{-k(x-d_0)}} \tag{4.6}$$

   where *x* represents the input of the function, which is the distance between vehicles in meters. *d_0* represents the threshold distance, expressed in meters. It represents the distance from which the strength of the proximity relation begins to decrease and *k* is slope coefficient of the logistic function. It determines how rapidly the proximity relation decreases as the distance increases. In Figure 4.5 we can see the see the proximity relation strength function with $d_0 = 25$ and *k = 0.5*

b) Theta function

   In our context, the theta function, represent a weigh measure to assess the relevance of an obstacle based on its relative position with respect to the direction of vehicle movement. The function $f_3(\theta)$ takes as input the angle θ, which represents the angular deviation between the orientation of the vehicle and the position of the obstacle. This reflects the

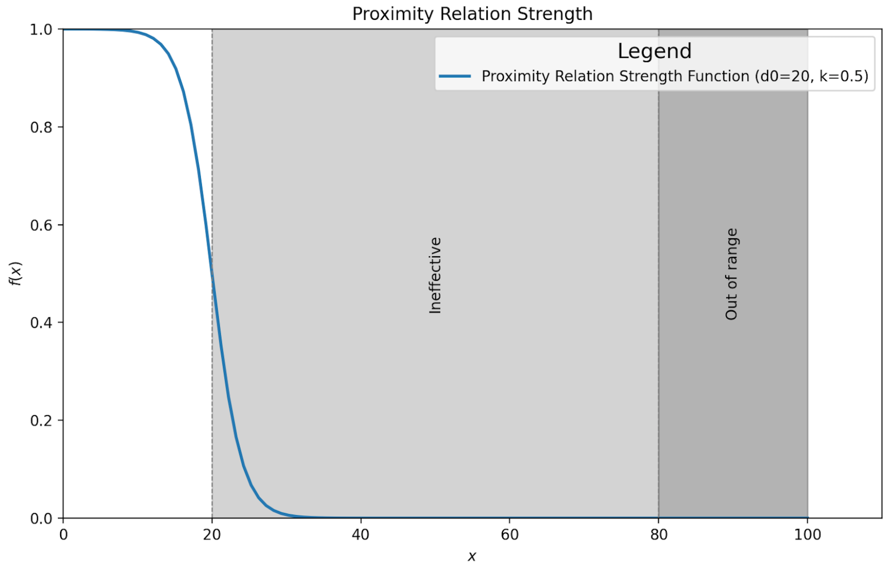


Figure 4.5: proximity relation strength function

intuitive notion that obstacles directly in the path of the vehicle assumes greater significance. For the *thetha function* we propose a piecewise-defined function formulated as follows.

$$f_3(\theta) = \begin{cases} 1 - 0.5\left(\frac{\theta}{45}\right) & \text{if } 0 < \theta < 45 \\ 0.5 & \text{if } 45 \leq \theta < 135 \\ 0.5 \cdot e^{-0.02(\theta - 135)} & \text{if } \theta \geq 135 \end{cases} \tag{4.7}$$

As depicted in the Figure 4.6, the importance tends to be higher when the object is located in the direction toward which the vehicle is heading.

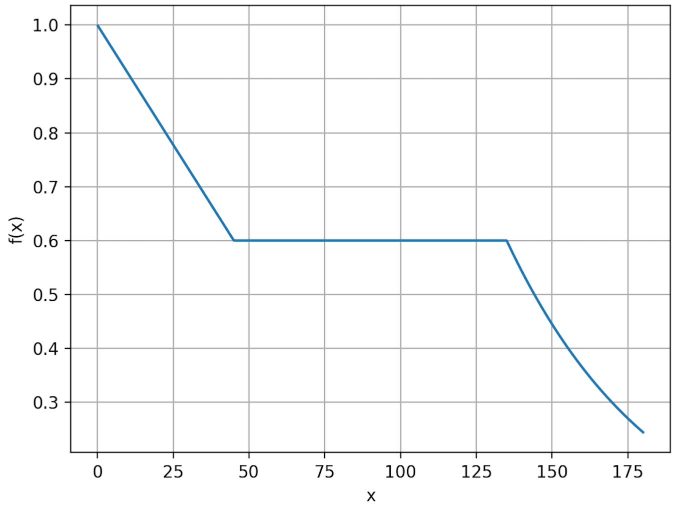


Figure 4.6: theta function

Overall VoI

Let's assign the values to the matrix to evaluate the weight of each attribute and consequently the total Value of Importance (VoI) for each obstacle. We assigned the values of the matrix according to the following criteria:

- $\alpha = 9$: High priority between the attribute of direction (*theta*) and the distance from the sender (*distance_sender*).
- $\beta = 7$: Moderate priority between the attribute of direction (*theta*) and the distance from the receiver (*distance_receiver*).
- $\gamma = 1/3$: Lower priority between the distance from the receiver (*distance_receiver*) and the distance from the sender (*distance_sender*).

It is now possible to calculate the pairwise comparison weights $w = \langle w_1, w_2, w_3 \rangle$ of the VoI attribute using Formula 4.5. The weights indicate the relative importance of each criterion or attribute compared to others in the decision-making hierarchy.

The results are shown in Figure 4.6.

Attribute	Value
w_1	0.785391
w_2	0.148815
w_3	0.065794

Table 4.6: Pairwise comparison weights $w = \langle w_1, w_2, w_3 \rangle$

Finally, to calculate the overall VoI, we need to aggregate the evaluations of each attribute. This involves summing all the weighted attribute evaluations obtained in the previous step. Here is the formula for aggregating the attribute evaluations:

$$\mathrm{v} = \sum_{i=1}^{n} w_i \times f_i \tag{4.8}$$

Where $w = \langle w_1, w_2, w_3 \rangle$ are the attribute weights in Table 4.5 and $f = \langle f_1, f_2, f_3 \rangle$ are the functions defined in the section Conditional VoI. The value of v represents the score of a single obstacle based on the specified attributes.

Image VoI and Image Ranking

Now that we're able to assign a value to each obstacle present in the image, we are interested in ranking the images obtained by each the vehicles within the CAV. After obtaining the quality values for all obstacles $v = \langle v_1, v_2, ..., v_3 \rangle$, where k is the number of obstacles detected in an image, the code computes the *Image VoI* by aggregating the quality values and adjusting them based on the number of perceived obstacles. The final VoI is derived from the mean of the quality values, scaled by a logistic function of the number of perceived obstacles. Mathematically, it can be expressed as:

$$\text{Image VoI} = \text{Mean}(v) \times \text{Logistic}(k) \tag{4.9}$$

The logistic function adjusts the mean quality value based on the number of perceived obstacles. It ensures that as the number of perceived obstacles increases, the importance of the perception data is appropriately scaled. The logistic function has the form:

$$f_{\text{n\_obs}}(k) = \frac{1}{1 + e^{-k\cdot(x-x_0)}} \tag{4.10}$$

where k is the slope parameter that determines how quickly the function transitions from one value to another and x_0. that is the midpoint of the function, where the transition occurs. Each vehicle within the CAV system will be able to generate a ranking of the acquired images based on their utility compared to other vehicles.

Evaluate optimized Method in Case study

We have defined a strategy for ranking the importance of data acquired by the vehicles' sensors. Now, let's evaluate the performance of this strategy in our case study. In Table 4.7, we have reported the values used for simulating the case study.

Parameter	Value
α	9
β	7
γ	$\frac{1}{3}$
d_0	25
k	0.5
$n_{\max}$	25

Table 4.7: Parameter AHP

Building upon the considerations outlined in the previous section, we establish a ranking for each vehicle, identifying the most critical images to receive along with their associated values. Table 4.8 shows the ranking for vehicle A, vehicle C and vehicle F receiving vehicles of the images collected by the vehicles within the network, classified in order of importance according to our considerations.

Based on these rankings, let's analyze the scenario for our case study. The Figure 4.5 shows the number of messages sent and received for each vehicle in the network along with the redundancy.

This prioritization scheme allows for more efficient utilization of bandwidth and computa-

Receiver A

Sender	Direction	Value
D	south	1.62243
C	south	0.90185
F	north	0.50589
D	north	0.48256
E	north	0.46831
E	south	0.45841
C	north	0.41679

Receiver C

Sender	Direction	Value
D	south	3.02016
A	south	0.60116
B	north	0.60114

Receiver F

Sender	Direction	Value
D	south	1.62243
B	north	1.01317
D	north	0.86299
C	north	0.85807
A	south	0.55586
A	north	0.46612
E	south	0.45845
C	south	0.39274

Table 4.8: Ranking for recevers A, C e F

tional resources, ensuring that vehicles receive the most pertinent information necessary. Table 4.4 presents the results of the proposed optimized dissemination algorithm. We can observe that:

Metric	Average distance
Total messages	17
Average distance [m]	22.89
Redundancy count	2.0
Redundancy (%)	11.76%

Table 4.9: OPT Simulation Results

- The value of 17 total messages suggests efficiency in communication, indicating that there was a relevant improvement in number of messages exchanged. This implies that our communication method is capable of transmitting necessary information with optimal use of communication resources.

- The average distance of approximately 22.72 units is in line with our expectations, as it is slightly worse than the broadcast value and is very similar to the semi-broadcast value. However, in this case we were able to greatly improve the number of messages exchanged compared to this last strategy.

- The redundancy percentage of 11.76% indicates that only a small portion of the total messages is redundant. This suggests that our method and strategy based on the ranking

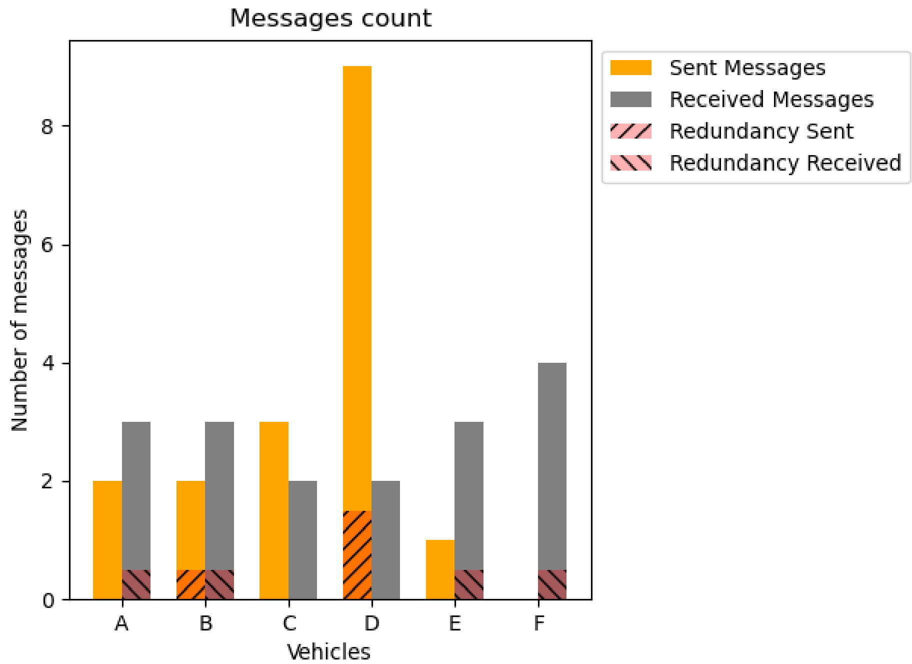


Figure 4.7: Count messages Optimized

of information has significantly reduced redundancy.

In summary, this advanced communication technique leverages the concept of VoI and employs the AHP methodology to prioritize the dissemination of obstacle information, thereby enhancing the overall effectiveness and efficiency of communication within the CAV system.

Chapter 5

Performance Evaluation

Now that we had the chance to go into the details of the case study and gained insight into the characteristics of our simulator, including its classes and underlying assumptions, we can now test and validate our dissemination algorithms using the Monte Carlo method and through a large number of simulations. Our objective is to evaluate the performance of our algorithms across various scenarios, conducting a multitude of tests and considering diverse parameters. We will define two configurations. Specifically, we will have one dataset that prioritizes high-quality images and another with a high number of obstacles. Finally, we will present the results plots of these simulations and evaluate the outcomes. Let's now revisit the parameters of our simulator and outline which of these will be modified to collect and evaluate our results.

Main Actors and Environment:

- *Number of AVs:* Specifies the how many AVs are present within the simulated environment.
- *Position of AVs:* Determines the initial positions of AVs within the scenario map.
- *Number of Obstacles:* Defines the quantity of obstacles, both static and dynamic, deployed throughout the simulated environment.
- *Position of Obstacles:* Specifies the locations of obstacles within the scenario map.

- *Scenario Map:* Describes the layout and features of the simulated environment, including roads, intersections, and other infrastructure elements.

Parameters of Analytic Hierarchy Process (AHP) for the proposed optimized dissemination algorithm:

- *Relative Preference Matrix:* Captures the pairwise comparisons of criteria and alternatives, reflecting the relative importance of each criterion in relation to others. [Default value: $\alpha = 9$, $\beta = 7$, $\gamma = \frac{1}{3}$]
- *Theta Function:* quantifies the interest of an AV relative to an obstacle based on the direction in which the vehicle is moving. [Default value: Function 4.7]
- *Proximity Relation Function:* quantifies the interest of a detected obstacle based on its proximity to the AV's sensor. [Default value: Function 4.6, d_0 = 25 , k = 0.5]
- *n_obs_function:* quantifies the importance of an imaged based on the number of detected obstacles. [Default value: Function 4.10, d_0 = 20 , k = 0.1]

5.1 Results

5.1.1 Generalization of the case study

Let's begin by presenting the results of our simulation. The following Table 5.1 and Table 5.2, we present the metrics of interest defined for each method. To conduct our analysis, we fixed the number of cars to 5 and the number of obstacles to 9, as it corresponds to the scenario presented in the case study in Chapter 4. We validate the results across a large number of iterations. By subjecting our simulation to a large number of iterations, via the Monte Carlo approach, we can enhance the credibility and validity of our study, enabling us to draw meaningful conclusions and insights from the data. For each iteration, vehicles and obstacles were randomly positioned within the defined spawn zones.

Parameter	**Value**
n_iteration	1000
n_car	5
n_obstacles	9
position_car	random
position_obstacles	random

Table 5.1: Case study generalization, Configuration Information

Parameter	Value
α	9
β	7
γ	$\frac{1}{3}$
d_0	25
k	0.5
$n_{\max}$	25

Table 5.2: Case study generalization, Parameter AHP

As previously mentioned, for the proposed optimized dissemination algorithm, we used the AHP method with the functions and matrix defined in Chapter 4. These parameters were maintained across all iterations of the simulation.

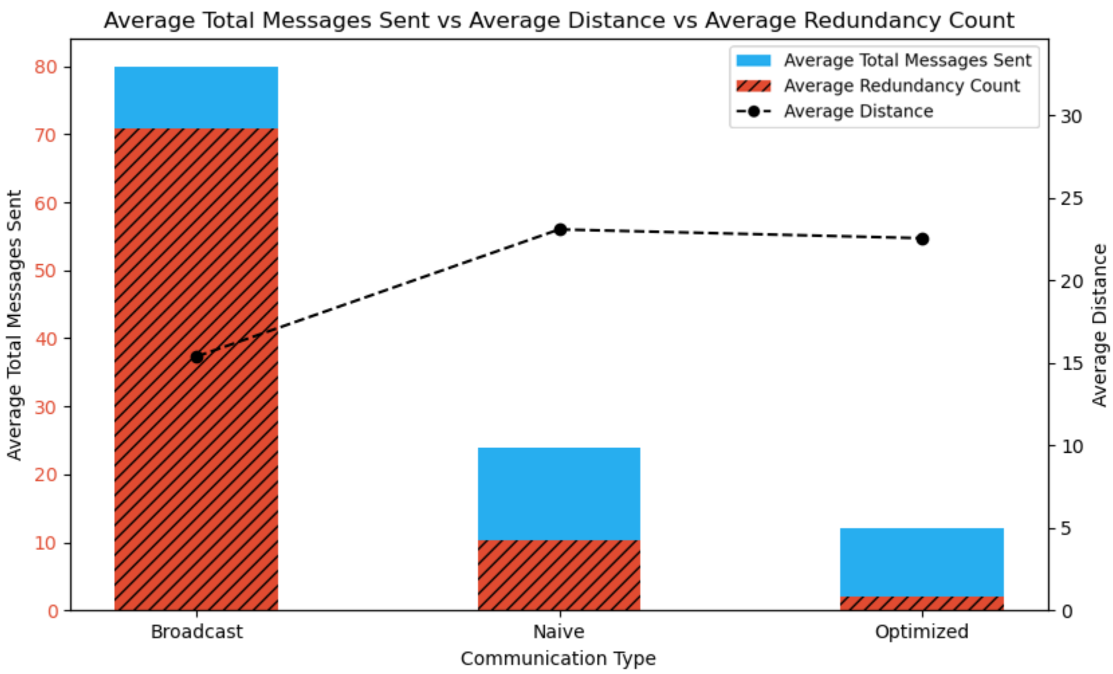


Figure 5.1: Case study generalization: Plot comparison of three methods: Total Message Count, Redundancy Percentage, and Average Distance

From the results in Figure 5.1 and Table 5.2 obtained by iterating over a large number of configurations, we observe that the overall performance aligns with the trends discussed in the case study. These findings suggest a level of stability in the outcomes across different simulation

	Broadcast	Naive	Optimized
Average Total Messages	80.0	23.814	12.607
Average Distance [m]	15.705	24.035	23.536
Percentage Average Redundancy	71.31	11.619	1.963

Figure 5.2: Case study generalization: values of interest

settings. Notably, the optimized method can significantly reduce redundancy and the number of messages exchanged within the network compared to the baseline schemes. Regarding the number of messages exchanged, we observe a significantly higher number of messages in the broadcast method compared to the Naive and Optimized methods. Specifically, the proposed Optimized algorithm demonstrates an 83% reduction in the number of messages sent compared to broadcast and a 45% reduction compared to the Naive method. Moreover, we note that message redundancy is substantially higher in the broadcast method compared to the Optimized method, with approximately 70% redundancy for broadcast, 11% for Naive, and less than 2% for Optimized. As expected, the average distance, representing the quality of obstacle data (given that sensors can acquire better images), is lowest for broadcast, as vehicles have access to all collected data, including the best quality. Meanwhile, it is higher and similar between the Naive and Optimized methods, despite the significant reduction in exchanged messages and redundancy achieved by the latter. We can conclude that the strategy employed in the Optimized method, by implementing a ranking strategy for information dissemination to potential receivers, allows a significant reduction in the number of exchanged messages and minimizes message redundancy. It is possible to observe a slight degradation in the quality of obstacle data; however, given the significant reduction in messages exchanged, the overall performance remains excellent. Moving forward, let's assess how the performance trends vary with changes in these parameters.

5.1.2 Results as a function of the simulation parameters

In the previous section, we have observed the results of our data dissemination algorithms using the default parameters of the AHP, as defined in section 4.2.4. However, several considerations can be made in the choice of these parameters, and depending on attributes intended to be prioritized, different results can be obtained in different scenarios. We will now define two simulation configurations: one prioritizing data quality over quantity of information and another prioritizing the number of detected obstacles over the quality of data obtained and we're going to evaluate the results.

First parameter configuration: quality data over quantity

The first parameter configuration prioritizes quality over quantity, placing significant emphasis on high-quality information. This configuration tends to prioritize clear and relevant images containing nearby obstacles. The parameters that exhibit these characteristics are α, β, and γ in the comparison matrix and the parameter k and $x_{0_{\text{set 1}}}$ for the logistic function are reported in Table 5.3. In Figure 5.3 we plot the resulting the logistic function (Equation 5.1) for the "number of obstacles" attribute.

Params	α	β	θ	k	$x_{0_{\text{slow}}}$
Values	9	7	$\frac{1}{3}$	0.1	20

Table 5.3: First parameter set: Parameter Values

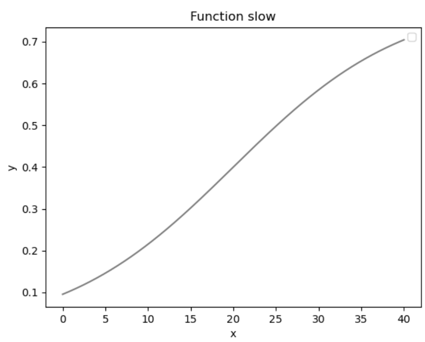


Figure 5.3: First parameter set: Logistic function $f_{\text{set1}}(x)$

$$f_{\text{set1}}(x) = \frac{1}{1 + e^{-k\cdot(x - x_0)}} \qquad (5.1)$$

Now, let's present the results obtained. Below are the plots of values calculated in our simulator with $n_{iter} = 1000$ Monte Carlo iterations. In Figure 5.4, we can observe the trend of exchanged messages and redundancy percentage as the number of obstacles varies for the three types of dissemination strategy. Here, we vary the numbers of obstacles $n_{obs} = \{10, 15, 20, 25, 30, 35, 40\}$. In Figure 5.5, we can see the same parameters as a function of the number of deployed AVs $n_{AVs} = \{3, 4, 5, 6, 7\}$. We can observe how the trend of the number of messages exchanged increases with the growth in the number of obstacles, as does the percentage of message redundancy, which stabilizes at around 25% for the opitimized method with 40 obstacles present. However, it is noteworthy that even with a high number of obstacles, although the number of exchanged messages and redundancy increases, it still remains significantly lower compared to the other two strategies, broadcast and naive. As for the trend concerning the variation in the number of vehicles, we can observe that the number of messages exchanged for the optimized method increases with the increase in vehicles. However, the percentage of redundancy stabilizes at 10% from 5 vehicles onwards. Meanwhile, for the naive method, the redundancy percentage increases significantly as the number of AVs increases.

In Figure 5.6, we present a comprehensive overview of the Optimized method in this first simulation configurations set. The plot illustrates the trend of the number of exchanged messages and the percentage of redundancy as the number of obstacles increases for three different values of n_{AVs} (3, 4, 7). Here, we can observe that, as expected, both the number of exchanged messages and the redundancy percentage increase with the growing number of vehicles and obstacles. However, the growth trend remains relatively low for both metrics, even with a high number of vehicles and obstacles.

Second parameter set: quantity over quality data

In this second simulations of parameters, we prioritize the quantity over quality, emphasizing the acquisition of a large volume of information. This choice tends to favor images that contain a high number of obstacles, even if of low quality.

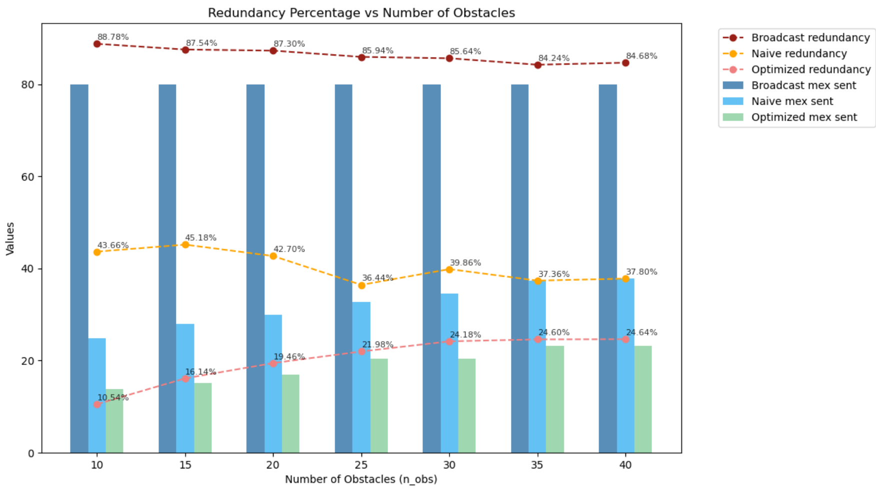


Figure 5.4: First parameter configuration: plot comparison of three methods: total message count, redundancy percentage and average distance, varying n_{obs}

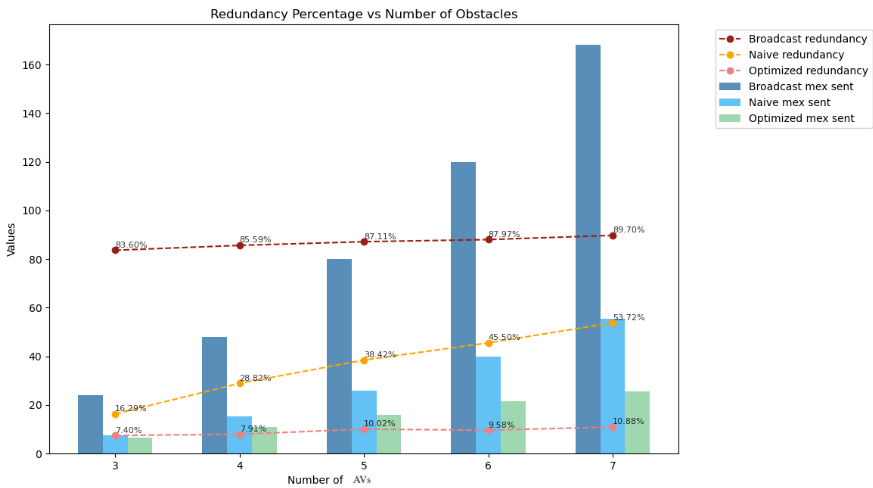


Figure 5.5: First parameter configuration: plot comparison of three methods: total message count, redundancy percentage and average distance, varying n_{AV}

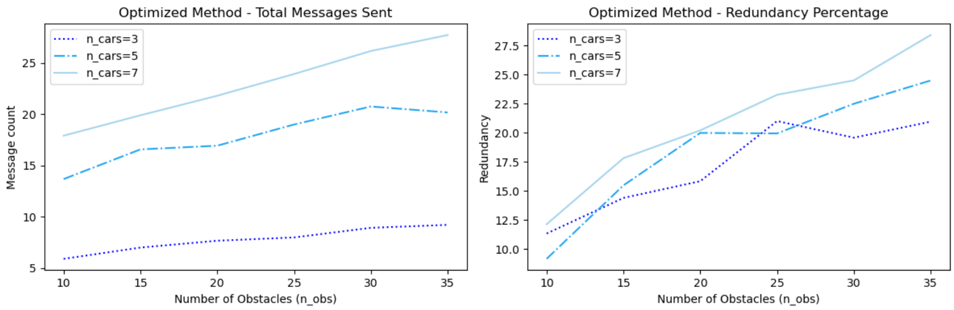


Figure 5.6: First parameter configuration: plot comparison of $n_{AVs} = \{3, 5, 7\}$, varying n_{obs} and varying n_{AVs}

In Table 5.4 we report the AHP parameters of the comparison matrix and of the logistic function. In Figure 5.7 we plot of the logistic function (Equation 5.2)for the "number of obstacles" attribute.

Params	α	β	θ	k	$x0_{\text{slow}}$
Values	3	$\frac{1}{9}$	$\frac{1}{5}$	0.5	5.5

Table 5.4: Second parameter configuration: Parameter Value

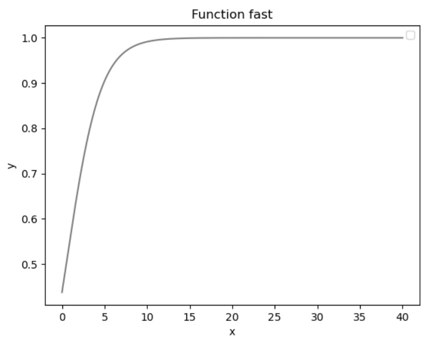


Figure 5.7: Second parameter configuration: Logistic function $f_{\text{set1}}(x)$

$$f_{\text{set2}}(x) = \frac{1}{1 + e^{-k \cdot (x - x_0)}} \qquad (5.2)$$

Let's present the results obtained with $n_{iter} = 1000$ Monte Carlo iterations iterations. In Figure 5.8 and in Figure 5.9 we can observe the trend of exchanged messages and redundancy percentage for $n_{obs} = \{10, 15, 20, 25, 30, 35, 40\}$ and number of vehicles $n_{AVs} = \{3, 4, 5, 6, 7\}$ varies. We can observe how the trend of the number of messages exchanged increases with the growth in the number of obstacles, but tends to stabilize above 35 obstacles. As for the trend concerning the variation in the number of vehicles, we can observe that the redundancy percentage is nearly constant, remaining below 10%, as the number of vehicles increases.

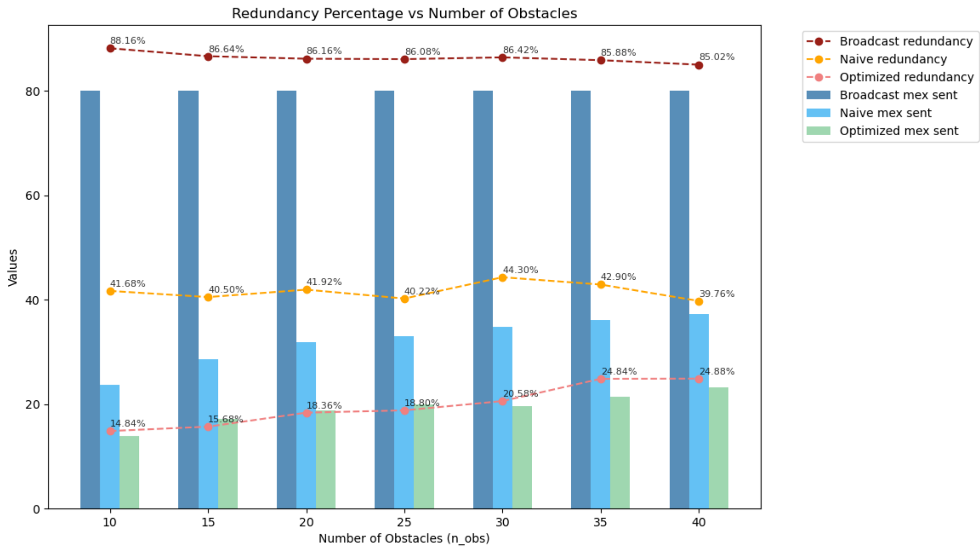


Figure 5.8: Second parameter configuration: plot comparison of three methods: total message count, redundancy percentage and average distance, varying n_{obs}

In Figure 5.10, we present a comprehensive overview of the Optimized method for this second set of simulations. Once again, the plot illustrates the trend of the number of exchanged messages and the percentage of redundancy as the number of obstacles increases for three different values of n_{AVs} (3, 4, 7). As expected, both the number of exchanged messages and the redundancy percentage increase with the growing number of vehicles and obstacles. However, the number of exchanged messages and the percentage of redundancy confirm that even with a different parameter set, the performance of the Optimized dissemination algorithm remain promising.

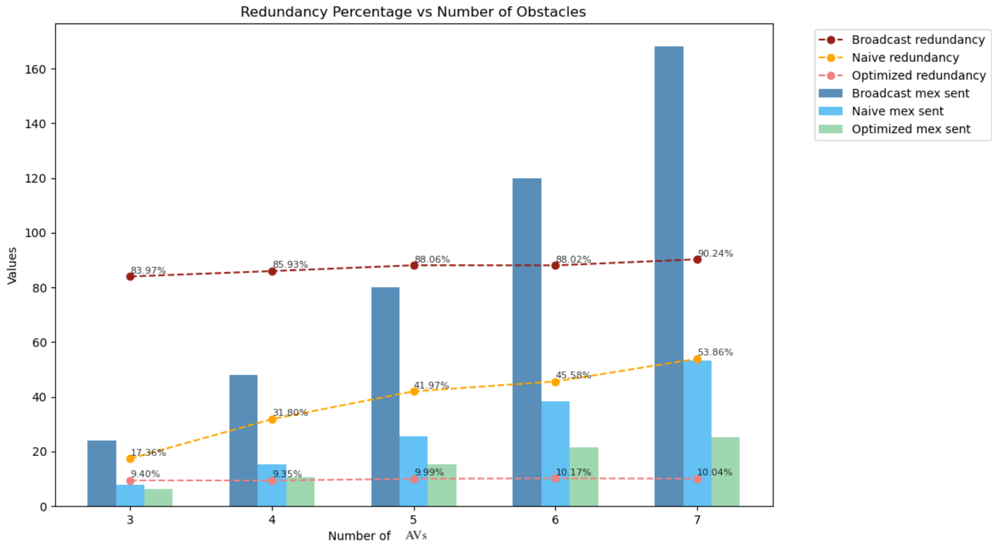


Figure 5.9: Second parameter configuration: plot comparison of three methods: total message count, redundancy percentage and average distance, varying n_{AVs}

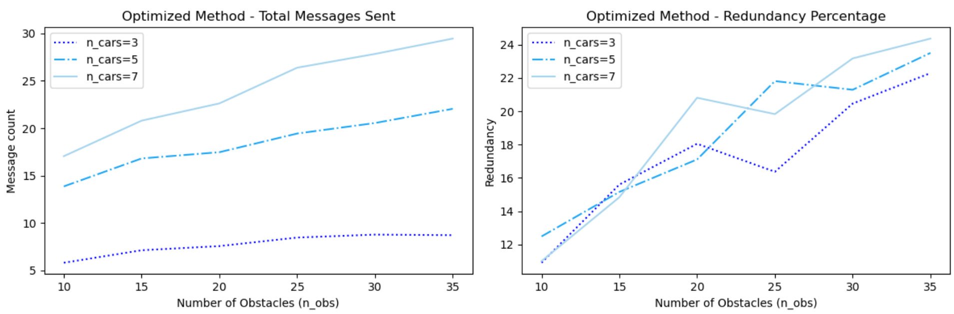


Figure 5.10: Second parameter configuration: plot comparison of $n_{AVs} = \{3, 5, 7\}$, varying n_{obs} and varying n_{AVs}

5.1.3 Final considerations

Let's consider our results. Thanks to the outcomes obtained and the simulator testing the performance in various scenarios with a high number of interactions and configurations, the proposed method appears to have promising potential in the field of data dissemination within connected autonomous vehicles.

In our simulations, we have successfully ensured that all intelligent vehicles are aware of all detected obstacles,and this research goal was achieved with a significantly lower number of messages exchanged compared to our benchmark algorithms (broadcast and semi-broadcast). Between broadcast and optimized methods, we managed to save an average of 78% of the total messages exchanged.

These results are indeed very encouraging. However, as we discovered during the development of the optimized method, particularly in defining the parameters of the AHP for calculating the VoI, the variables involved in the framework are numerous and diverse. Moreover, the scenarios that may arise in the real world are even more varied. In this chapter, we attempted to define parameters that would yield results for evaluating the VoI differently, depending on whether one prioritized image quality or quantity.

The analysis of results obtained through simulations of these two parameter configuration reveals subtle differences performance in specific scenario configurations. Upon comparing Figures 5.4 and 5.8 when varying the number of obstacles, we can observe that the first set of simulations (where quality is prioritized), results in a lower redundancy percentage with respect to the second set of simulations (where quantity is prioritized instead). For example, we can observe that for 10 obstacles, the redundancy percentage is 10.54% for set the first set and 12.84% for second set. However, as the number of obstacles increases, we obtain higher average values of messages and redundancy (when we have between 15 and 30 obstacles), which stabilize at similar values around 24.7% for numbers of obstacles greater than 40.

By comparing Figures 5.5 and 5.9 as concerning the variation in the number of vehicles, we can observe that parameter configuration 2 maintains a constant redundancy percentage. While for low numbers of vehicles, we observe lower redundancy for parameter configuration 1. Both sets stabilize at around 10% with more than seven vehicles. We can appreciate an improvement of approximately 2% for low vehicle numbers (3, 4) when obstacles are constant, and a notable enhancement of about 15% for obstacle numbers ranging from 15 to 25 using the second set of parameters that prioritize quality. We can observe that for three vehicles, the redundancy percentage increases from 7.40% for the first set to 9.40% for the second set, and similarly from 7.91% to 9.35% for the case with four vehicles.

Based on these considerations and on the comparison of Figure 5.6 and 5.10, we can conclude that parameter configuration 1, which prioritizes quality, is preferable when the number of vehicles is low, less than 35, and the number of obstacles is also low. On the other hand, parameter configuration two, which prioritizes the quantity of information, is preferable in scenarios with many obstacles and many vehicles.

Chapter 6

Conclusions and future works

In this thesis, we have explored the potential enhancements in traffic awareness facilitated by collaboration among AVs through cooperative perception. Our primary objective was to minimize the volume of sensory data shared among AVs while ensuring comprehensive perception of the environment, particularly in detecting all potential obstacles in the proximity of the AVs. To achieve this goal, we have investigated the concept of VoI in vehicular networks and proposed a framework that assigns priorities to the sensory data collected onboard AVs based on various scoring functions using the Analytic Hierarchy Process (AHP) method. These functions evaluate factors such as the distance between AVs and obstacles, the relevance of data to the direction of the receiver, and the quality of the sensory data.. Our proposed algorithm prioritizes message transmission in contrast to baseline schemes that transmit data immediately upon generation without prioritization. The simulation results demonstrate the efficacy of our algorithm in reducing the number of transmissions required to achieve full perception, with only minor degradation in the accuracy of detected obstacles. This reduction in transmission volume signifies a more efficient utilization of network resources and a potential improvement in overall system performance.

Future research in this area could involve further optimization of the prioritization algorithms by the definition of other parameters that can be taken into consideration and the selection of values that are suitable for various types of scenarios. Developing adaptive strategies that dynamically adjust data dissemination priorities based on changing traffic conditions, environmental factors, and vehicle dynamics could also be a focus. Finally, contributing to standardization efforts within the automotive industry to facilitate widespread adoption and interoperability of cooperative perception technologies across different vehicle manufacturers and communication protocols would be valuable. Addressing these areas of future research could advance the state-of-the-art in cooperative perception for autonomous vehicles and contribute to safer, more efficient transportation systems.

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