Feature-Based Vehicle Identification Framework for Optimization of Collective Perception Messages in Vehicular Networks

Hidetaka Masuda, Oussama El Marai, Manabu Tsukada, Tarik Taleb, *Senior Member, IEEE*, and Hiroshi Esaki, *Member, IEEE*

***Abstract*—The world is moving towards a fully connected digital world, where objects produce and consume data, at a sultry pace. Autonomous vehicles will play a key role in bolstering the digitization of the world. These connected vehicles must communicate timely data with their surrounding objects and road participants to fully and accurately understand their environments and eventually operate smoothly. As a result, the hugely exchanged data would scramble the network traffic that, at a given point, would no longer increase the awareness level of the vehicle. In this paper, we propose a vision-based approach to identify connected vehicles and use it to optimize the exchange of collective perception messages (CPMs), in terms of both the CPM generation frequency and the number of generated CPMs. To validate our proposed approach, we created a CARTERY framework that integrates SUMO, Carla, and OMNeT++. We also compared our solution with both baselines and European Telecommunications Standards Institute solutions, considering three main KPIs: the channel busy ratio, environmental awareness, and the CPM generation frequency. Simulation results show that our proposed solution exhibits the best trade-off between the network load and situational awareness.**

***Index Terms*—Carla, Collective perception message optimization, Intelligent transportation system, OMNeT++, SUMO, Vehicle identification, Vehicle to everything communication.**

I. Introduction

OVER the last decade, there have been significant breakthroughs toward enabling automated systems in different sectors, including medicine, industry, and transportation. Specifically, the prominent advances witnessed in mobile broadband networks (4G LTE), as well as the promising 5G performance, and breakthroughs in the artificial intelligence (AI) have significantly contributed to the introduction of automation into many aspects of our daily life. Intelligent transportation systems (ITS), and particularly the Internet of Vehicles (IoV) [1], is one of the beneficiary domains from these technological advents, where automation is deemed to be a better alternative to humans by considerably reducing human errors as well as the time-to-reaction at decision making [2], [3], [4].

Autonomous systems are capable of deciding for themselves what to do and when to do it [5]. To this end, they should be aware of their surroundings within a given spectrum. In the case of autonomous vehicles, this is achievable using different sensing devices such as radar, LiDAR, and cameras. Additionally, they need to constantly exchange messages and share relevant data available within their scope with other autonomous vehicles via vehicle-to-vehicle (V2V) communications, as well as with the infrastructure (e.g., roadside unit (RSU) via vehicle-to-everything (V2X) communications) [6], [7], [8], [9], [10], to increase their own, as well as other vehicles, situational awareness, notably at blind spots.

The ITS station reference architecture, proposed by the European Telecommunications Standards Institute (ETSI), provides the protocol stack for V2X communications. As part of the proposed architecture, the facilities layer provides ITS applications with common functions and handles the transmission of infrastructure-related messages, such as cooperative awareness messages (CAMs) [11] and collective perception messages (CPMs) [12], [13]. While CAM messages contain the sender's status, such as the speed and heading direction, CPM messages include additional information about objects perceived from sensor data, such as cars and pedestrians.

To further increase both the vehicles' awareness and the trustworthiness of the V2X data, the V2X-sensor fusion technique can be employed. It consists of combining the received information with the locally sensed data at the vehicle, ultimately to determine the Communication ID (e.g., the network address) of the perceived connected vehicle. Many ITS applications, such as cooperative adaptive cruise control (CACC) and maneuver coordination, require the Communication ID to initiate communication among connected vehicles. According to the technology consulting firm Gartner, Inc [14], it is expected, in the near

Manuscript received 3 February 2022; revised 26 May 2022; accepted 14 August 2022. Date of publication 4 October 2022; date of current version 13 February 2023. This work was supported in part by the European Union's Horizon 2020 Research and Innovation Programme through CHARITY Project under Grant Agreement 101016509, in part by the Academy of Finland Project 6Genesis under Grant Agreement 318927, and in part by JSPS KAKENHI under Grants 19KK0281 and 21H03423. The review of this article was coordinated by Prof. Xianbin Wang. *(Corresponding author: Tarik Taleb.)*

Hidetaka Masuda, Manabu Tsukada, and Hiroshi Esaki are with the Graduate School of Information Science and Technology, The University of Tokyo Tokyo 113-8657, Japan (e-mail: hide@hongo.wide.ad.jp; tsukada@hongo.wide.ad.jp; hiroshi@wide.ad.jp).

Oussama El Marai is with the Department of Communications and Networking, School of Electrical Engineering, Aalto University, FI-02150 Espoo, Finland (e-mail: oussama.elmarai@aalto.fi).

Tarik Taleb is with the Faculty of Information Technology and Electrical Engineering, Oulu University, FI-90014 Oulu, Finland (e-mail: tarik.taleb@oulu.fi).

Digital Object Identifier 10.1109/TVT.2022.3211852

future, that over 5.8 billion endpoints, including IoT devices, will be in use across various market segments, such as automotive, government, and healthcare providers. Accordingly, overall data growth is outpacing the network capacity growth, which calls for devising new mechanisms and approaches to efficiently deliver only the needed data to its consumers in a timely fashion.

This paper leverages the V2X-sensor fusion approach to mitigate the CPM redundancy problem. The ultimate goal is to reduce the amount of generated and transmitted traffic, including the generation rate, by connected vehicles without compromising the vehicles' situational awareness. Although CPM redundancy mitigation was introduced in ETSI TR [15], however, no specific methods have been proposed to achieve it. Our proposed method uses the visible features of the perceived vehicles, detected by local sensors, to determine their Communication ID. Next, V2X data is fused with locally sensed data, so that all previously identified vehicles that have exchanged CAM messages will not be considered in future CPMs.

The contributions of this paper are three-fold. First, we propose a new vehicle identification framework based on the visible features of the vehicles. A key advantage of the proposed method is the constant ID derived from the visible features. More importantly, the derived ID does not violate the vehicles' privacy making the proposed framework compliant with the pseudonymization approach of V2X architecture. Second, we apply the proposed vehicle identification method to the object self-announcement redundancy mitigation rule (OSARMR) [15], and assess its effectiveness based on the channel busy ratio (CBR) and situational awareness. Third, we develop a new simulation framework, named CARTERY, to evaluate the proposed vehicle identification solution and its application to the OSARMR. CARTERY integrates three types of simulators, namely (a) *physical*, for generating sensor data such as LiDARs and cameras, (b) *network*, for the transmission of V2X data, and (c) *traffic* simulator, to imitate real traffic. The comparison of the proposed method against baseline and ETSI's CPM redundancy mitigation approaches proposed in [15], namely perceived object container inclusion management, demonstrates its superiority in dense environments of connected vehicles in terms of network load and situational awareness, particularly at high market penetration rates (MPR).

The remainder of this paper is organized as follows. In Section II, we discuss some related work concerning the three main contributions of this paper. Section III describes some use cases underpinning this study. The system design of the vehicle identification framework is detailed in Section IV. Section V provides the architecture of the developed CARTERY simulation framework, followed by the performance evaluation. Finally, Section VII concludes this paper, discusses the limitation of this work, and eventually highlights some future research work.

II. LITERATURE REVIEW

As discussed in the previous section, the contributions of this work are three-fold. Below we review the related work and potential pitfalls associated with each contribution. Among our contributions is the created CARTERY simulation framework, which provides the basis for discussion about existing simulation environments in this section.

A. Vehicle Identification of Perceived Vehicle

The authors of [16] propose a GPS-based vehicle identification system that employs relative position measurement derived from radar data. Considering the fact that GPS coordinates are subject to non-negligible errors, they are only used to narrow down the list of candidates. A more accurate method, namely the relative position tracking method over a short period, is then employed for vehicle identification. While simulation results demonstrate that vehicles can be identified with an accuracy rate of 93 %, it also reveals that it takes a few seconds (3 seconds) for the identification process to take place, which is considered a limitation for this work.

Researchers in [17] developed a more real-time method that uses ultra-wideband (UWB) sensors, to measure the round-trip delay of signals and the distance between vehicles [18], in addition to radar and GPS data.

In this study, the authors use statistical models to account for measurement errors, and the simulation results show the possibility of identifying a vehicle within 0.26 s, whilst 99 % of the identification was roughly performed in 1.3 s. Owing to the short-range communication limitation of the UWB sensors [19], [20], [21], this method is only applicable to adjacent vehicles (i.e., those behind or ahead).

A major limitation of the work discussed above is the omission of communication delay, which increases the GPS measurement errors, especially when a vehicle moves at a high velocity. To overcome this inherent limitation, other studies leverage image recognition techniques to extract relevant features from captured images of detected vehicles.

Masuda et al. proposed an identification method for vehicles using their license plates [22]. The latter consists of a unique visual feature for every vehicle that could be used to instantly identify vehicles by performing image recognition on the stream captured by the local camera. A proof of concept has been implemented and applied to Japanese characters and numbers. The recognized plate numbers were embedded in CAM messages where both GeoNetworking [23] and BTP [24] protocols, proposed by ETSI, were used for communication. Based on experimental results, only 17% of the objects were correctly identified from the image recognition process, mostly due to the small size of the characters. High image resolutions are, however, expected to yield higher accuracy rates.

B. CPM Redundancy Mitigation

As discussed earlier, road participants can be perceived and, consequently, broadcast by many vehicles via CPM messages. As a result, the network traffic would thus become congested without enhancing situational awareness. This section presents previously conducted studies in this field.

The authors of [25] proposed two different approaches to mitigate data redundancy, namely dynamic- and frequency-based approaches. In this study, the authors examine the trade-off between the content of CPM messages (i.e., to reduce the size) and how frequently they are generated based on the dynamics of the perceived objects. Simulation results revealed the effectiveness of the proposed rules in achieving a good balance between transmitted messages and network load. The proposed solution was evaluated under challenging conditions, including realistic and artificial setup scenarios. In a realistic traffic scenario, the message size, CBR, and the number of known objects were analyzed. Regarding the number of successfully identified vehicles, a marginal improvement was noticed. However, the message size was reduced compared to the CPM generation method without filtering objects, while CBR was significantly reduced to less than 50 % on average, which show that the proposed method can reduce network traffic without impairing the environmental awareness of the vehicles. This solution is similar in spirit to the mitigation method proposed by ETSI [12], which is based on both the frequency and dynamics. Besides, it considers other road participants that do not have wireless communication modules, such as pedestrians and animals, and periodically broadcasts information about the non-connected objects (i.e., every 500 ms for persons or animals, otherwise 1 s interval is used). In [26], the authors conclude that reducing the CPM of connected vehicles significantly reduces the CBR as well as the message size, especially at high MPR, yet the identification of connected vehicles was not considered in the study.

C. Simulation Environment

Simulation frameworks, which include physical and network environments, define the most common method for evaluating different approaches to optimize V2X communications among connected vehicles. This section describes different simulation frameworks and products used in previous research on ITS, such as game engines [27], [28], [29], [30] for the physical environment and Artery [25], [26] for V2X communications.

In [31], the simulation tools SUMO, OMNeT++, and Webots were used for simulating vehicle traffic, V2X network and the physical environment, as well as the vehicle dynamics, respectively. While the Veins extension enables synchronizing OMNeT++ and SUMO, Webots allows sending CPMs of the sensed data from the simulated vehicle. In [32], NS3, MATLAB, Simulink, and CarMaker were combined to simulate the cyber and physical environments. CarMaker and NS3 are used to simulate the vehicle dynamics and LTE network, respectively, while MATLAB and Simulink are used as interfaces to link NS3 with CarMaker. The major limitation of this setup is that V2X communications, based on ETSI ITS-G5 [33], are not supported. Moreover, some of the simulators are proprietary, which makes it difficult to verify their validity from the source code.

III. Use Cases and Problem Statement

To improve overall autonomous driving safety, vehicles must be timely aware of their surroundings to the maximum extent possible, so they can instantly react when something happens. This objective is achievable by constantly exchanging messages with road participants as well as the infrastructure. There are, however, many objects (e.g., legacy vehicles, humans, and animals) that are not connected, hence, cannot communicate and exchange signals. In such cases, connected vehicles should use different sensors (e.g., LiDAR and camera) to detect and avoid potential dangers, such as pedestrians crossing the road. This information will be communicated to other connected vehicles, using CPM messages, on the same spot to alert them preemptively. However, multiple connected vehicles may simultaneously perceive the same object (e.g., in crowded areas) and may end up unnecessarily exchanging duplicated information about road participants, causing traffic congestion and resource wastage, which, in turn, adversely impacts timely communication.

In this section, we discuss some ITS-related use cases that require vehicle identification, followed by the necessary features' properties for associating the network address to the detected vehicle. Fig. 1 illustrates the use cases discussed in this section.

A. Use Cases

The vehicle identification process is vital for many ITS applications. In this section, we describe some relevant ITS use cases that require the ID of perceived vehicles to accomplish their respective goals.

1) Cooperative Adaptive Cruise Control (CACC): Cooperation is crucial in vehicular networks to enable various autonomous driving functions [34], such as CACC. The latter relies on V2V communication to ensure timely acceleration and deceleration of vehicles that belong to the same platoon. In this scenario, the following vehicles must be able to intercept any intruder vehicle that may hook into the platoon, which may have detrimental effects. By using V2X-sensor fusion, it would be possible to obtain the Communication ID of the preceding vehicle, enabling the verification of its legitimacy within the platoon.

2) Road Monitoring: The vehicle identification can also be used for remote assistance (e.g., remote driving or stopping safely) when vehicles need help. For instance, an RSU can detect a misbehaving vehicle (e.g., a driver is down owing to sudden illness) and extract its Communication ID, by leveraging V2X-sensor fusion, which is then supplied to the remote operator to establish a connection to the vehicle and take over driving duties from the onboard driver.

3) Maneuver Coordination: Maneuvers coordination service uses traffic rules to orchestrate, for example, the conflicting future trajectories and overtaking maneuvers [35], [36] of autonomous vehicles, thereby ensuring road safety and preventing accidents. To this end, connected vehicles share their maneuver information with other connected vehicles, via V2V or V2X communications, and conflicts between their respective trajectory paths can be resolved through negotiations. As shown in Fig. 1, the red vehicle declares that it will give way to the green vehicle, and any maneuver that would contravene that declaration may cause an accident. In this case, the green vehicle needs to verify that the received CAM message, indicating that the red vehicle will give way, comes from the red vehicle in front of it, and not from another vehicle on the same spot, likely

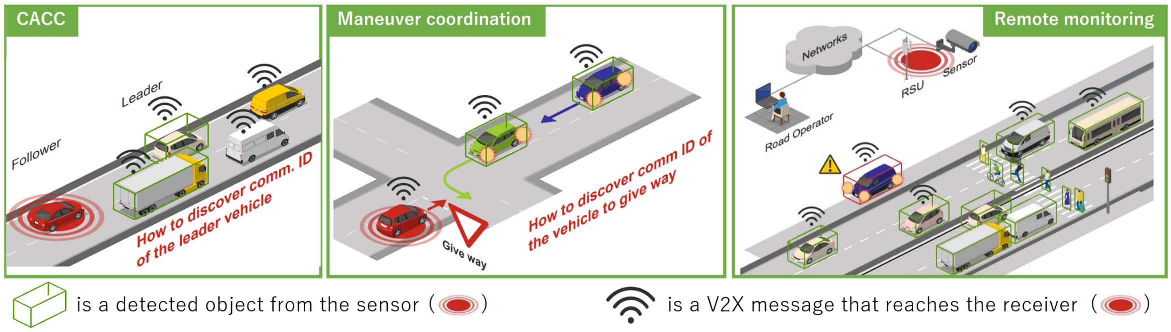

Fig. 1. Use cases of vehicle identification.

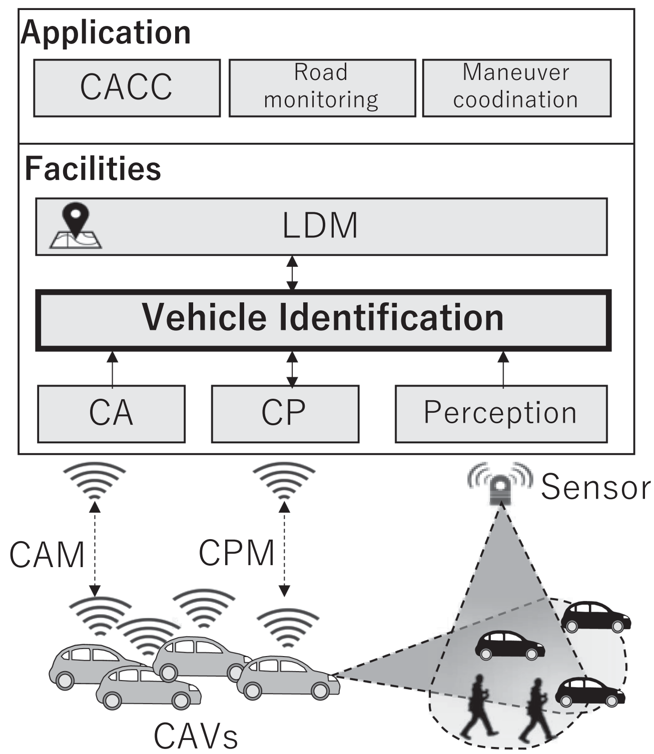

Fig. 2. Overall architecture of the vehicle identification framework.

with the same characteristics (e.g., color and brand). To achieve this, vehicle identification could be used to associate the received information (i.e., the declared trajectory) with the perceived data (i.e., the detected and recognized vehicles) by using the front camera of the green vehicle.

4) CPM Redundancy Mitigation: Using CPM messages, connected vehicles can share sensed data (such as detected legacy vehicles or pedestrians crossing the road) between each other to enhance their situational awareness. Instead of sending raw sensor data, it is important to include in CPMs only the extracted features from detected objects to reduce network usage. Often, however, the same object is seen by different vehicles from different angles, causing the same data to be transmitted multiple times. In addition, if the detected object is a connected car, similar data is received via CAM messages. These redundant messages would contribute to the exhaustion of the V2X communication channels, including ITS-G5 and LTE-V2X, and the waste of vehicles' computation resources. It would be then possible to leverage V2X-sensor fusion to obtain the Communication IDs of the connected objects and only send CPM messages regarding non-connected objects, while information about connected objects is received via CAM messages.

B. Requirement Analysis

This section defines the four main properties of vehicle features required for vehicle identification in this research work.

1) Data are to Be Internally Retrievable: The data to be shared via V2X communication should be retrieved internally. These data can be either static (e.g., vehicle type, plate number, and Communication ID) or dynamic (e.g., position and speed). While static data are stored locally and do not change over time, dynamic data require accurate synchronization, should be constantly measured, and associated with timestamps.

2) Data are to Be Externally Perceivable: Connected vehicles are equipped with several sensors, such as LiDAR and cameras, that capture data regarding the surrounding environment (e.g., the road participants). The captured data via these sensors are labeled as externally perceivable data. Similarly, these data can be either static (e.g., vehicle color and number plate) or dynamic (e.g., position and speed).

3) Static Data: Dealing with dynamic data requires very accurate time synchronization, which is highly challenging, notably at high velocity. For this reason, we only consider static data in this study.

4) Unique Data: The data uniqueness within the vehicle's perception range is essential for instant data association. In general, vehicle characteristics, such as color and brand, are not unique per vehicle. Geolocation can be combined with other visible data to achieve data uniqueness, but it bears the disadvantage of inherent measurement errors and a slow association process.

IV. Vehicle Identification Framework

This section describes the proposed framework for identifying connected vehicles, which employs a feature-based approach. It consists of evaluating the similarities between the sensor and

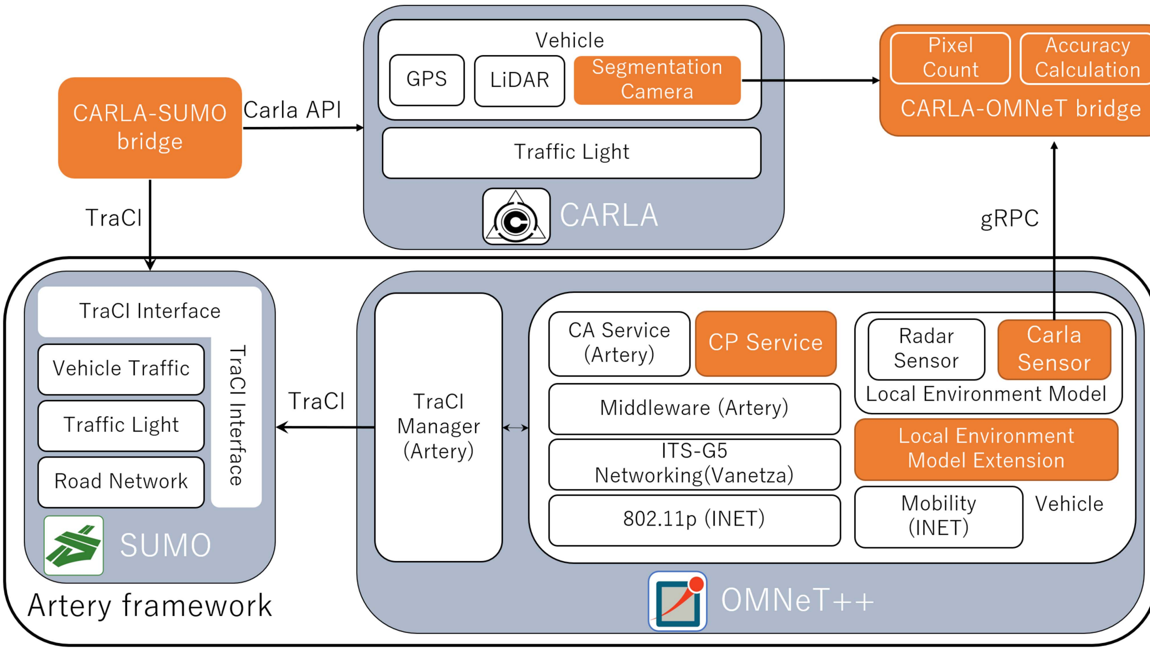

Fig. 3. Architecture of the envisioned CARTERY framework.

V2X data, acquired via onboard cameras and CAMs or CPMs, respectively, to extract the vehicle ID of the perceived vehicles.

Fig. 2 illustrates the overall architecture of the proposed vehicle identification framework. This figure shows two main layers, namely facilities and applications. According to the ITS station reference architecture, the facilities layer provides the core functionalities, such as local dynamic maps (LDM), cooperative awareness (CA), and collective perception (CP) services, which are used by various ITS applications (e.g., maneuver coordination and CACC).

As part of this framework, we propose adding a new facility layer module, called Vehicle Identification. With only visual information (e.g., color, vehicle brand, plate number), this module can identify a perceived vehicle and extract the Communication ID of the connected cars. Towards this end, we propose to encode the visual features of the sending connected vehicle, which can be retrieved locally, as a vector and embed it in the Station ID field of CAM or CPM messages. At the receiving cars, we extract from CAMs and CPMs, via CA and the CP services, respectively, both the Station ID and the Communication ID, and save them into the local database, also called LDM. Information in this database includes a static map of the environment and positions of nearby vehicles, which is used by ITS applications (e.g., CACC and maneuver coordination) to establish communication with other vehicles. Following ETSI standards, and due to privacy issues, the Communication ID keeps changing over time. Accordingly, we keep updating the Communication ID field in the LDM, using the constant Station ID that contains the visual features of the vehicles. Likewise, visual features extracted from detected vehicles using local sensors (i.e., cameras) are combined to generate an ID for the perceived vehicle. The latter is then compared against the existing Station IDs (i.e., extracted from the CAMs and CPMs) in the LDM using the Euclidean distance, and the association between the received and perceived data occurs when the Euclidean distance falls below a threshold only.

The proposed vehicle identification framework based on the vehicle's visual features fulfills all four requirements stated in Section. III-B. Since the appearance of the vehicle does not change over time, this verifies the property of being static. Also, it could be saved in the vehicle's local storage when shipped from the manufacturer, so the appearance is locally retrievable at any time. The visual information can also be retrieved using image recognition techniques by surrounding vehicles via their onboard cameras, which verifies the property of being externally perceivable. Similarly, uniqueness can be achieved when various perceived features of the vehicle, such as plate number, brand, and geolocation, are considered together.

According to current V2X protocol specifications, there are no dedicated fields for communicating the visual information of vehicles. To avoid any proposal for altering the current V2X communication protocol, we encode the visual information in the Station ID since, to date, no guidelines have been published on how to use this field. Finally, it is worth emphasizing that we adopted a distributed system in the proposed architecture to avoid the single point of failure (SPOF) design flaw. Nevertheless, this architecture can be adapted easily to leverage edge computing technology, such as RSU, to enhance overall system performance in terms of accuracy and situational awareness, as well as storage capabilities.

V. CARTERY SIMULATION FRAMEWORK

To evaluate our proposed framework, we created the CARTERY simulation framework, which integrates three different simulators, namely SUMO, Carla, and OMNet++, for simulating the traffic, physical environment, and communication network, respectively. SUMO is the traffic simulator that is used to simulate the vehicle's route and speed. As the proposed vehicle identification framework mainly relies on extracting the visible features of the perceived vehicles, we use Carla to simulate the local perception of the camera, considering the occlusion of vehicles. The third simulator, i.e., OMNet++, is used to simulate V2X communications and exchange CPM messages.

Carla [37] is an open-source autonomous driving simulator developed to support research and validation activities. It simulates 3D objects (e.g., vehicles and buildings) using Unreal Engine 4, and local sensors such as LiDAR and depth cameras. It officially supports integration with SUMO and offers APIs to control vehicles in two popular programming languages, namely Python and C++. Existing V2X simulators assume 100% detection accuracy when the vehicle is in line of sight within a certain range. By contrast, as part of our goal in this research, we want to simulate the impact of detection errors on CPM redundancy mitigation through different identification accuracy rates. These errors might arise from various factors such as the hardware performance (e.g., CPUs and GPUs), the machine learning models used to extract the IDs from the vehicles' visual information, the vehicle occlusion, the foggy weather, and the low-resolution of the captured images.

Artery [38] is an open-source V2X simulation framework used to simulate V2X communication and vehicle traffic. Its design is based on the ETSI ITS-G5 reference architecture [39], and it integrates OMNeT++ [40] and SUMO [41]. It also provides middleware for sharing information among V2X services. OMNeT++ is a C++ discrete-event simulation framework wherein simulation modules are developed independently. The INET module inside OMNeT++ allows simulating the wireless link layer protocol for V2X communication, while Vanetza [42] is used to simulate the ETSI ITS-G5 protocol stack. These modules allow simulating the communication range, delay, and congestion within OMNeT++. TraCI is another module of OMNeT++ that serves as an interface between OMNeT++ and SUMO. The latter allows simulating and controlling the vehicle's location and motions, as well as the signal of traffic lights.

$$\varphi = \begin{cases} 0, & (pixels \leq \lambda) \\ \zeta, & (pixels > \lambda) \end{cases} \tag{1}$$

Fig. 3 depicts an overview of the overall architecture of the created simulation framework, wherein the white boxes show the existing modules of the integrated simulation frameworks, and the orange boxes represent the modules we developed to integrate Carla with Artery. *CarlaSensor* is a sensor module we implemented in Artery to make it possible for vehicles in OMNeT++ to fetch sensor information from Carla. In the proposed framework, we simulate the vehicle identification module, assuming that it succeeds given a model accuracy ζ, as shown in (1), where $pixels$ represents the number of visible pixels in the vehicle's image, and φ is the corresponding vehicle identification accuracy percentage when the vehicle visibility is greater than a given threshold λ. As discussed above, our evaluation of the proposed vehicle identification framework accounts for detection errors and assesses its impact on environmental awareness and network load. To this end, based on the vehicle's visibility, expressed by the number of pixels in the captured image, we define three vehicle identification rates, namely 60%, 80%, and 100%.

Algorithm 1: Algorithm Executed in each Vehicle.

```
while True do
    foreach CAM in CAMs do
        ExtractFields(CAM) /* e.g.,
            Station ID, position          */
        UpdateLocalDatabase(LDM);
    end
    p ← GetSemanticallySegmentedPicture();
    VehiclesPixels, StationIDs ←
      ExtractDataFromGroundTruth(p);
    foreach (pixels, StationID) In (VehiclesPixels,
      StationIDs) do
        if (pixels > ∂) and (random(0,1) >
          ξ) and (VehicleFoundInLDM(StationID))
          then
            ExcludeVehicleFromNextCPM()
        else
            IncludeVehicleIntoNextCPM()
        end
    end
    SendCPM();
end
```

The pseudo algorithm that runs in each connected vehicle is given in Algorithm 1. Each time a CAM message is received, we extract the different fields, such as the Station ID and position, and then build/update the vehicle-specific LDM database. Next, it continually acquires semantically segmented pictures, and from each picture p, it extracts from the ground truth images all the pixels ($VehiclesPixels$) of the detected vehicles, as well as the Station IDs ($StationIDs$). Thereafter, only the detected vehicles that have a high resolution (1st condition in the if statement) as well as high identification accuracy (2nd condition), will be compared against the LDM database (3rd condition). The vehicles that have their Station ID stored in the LDM will eventually be excluded from the next CPM message; otherwise, they will be included.

VI. Performance Evaluation

A. Simulation Setup

To demonstrate the relevance and effectiveness of our proposed vehicle identification method in mitigating the CPM redundancy, we extensively evaluated and compared our approach to the one proposed by ETSI [15]. A view of the street layout from the simulated environment is shown in Fig. 4, where experiments took place on the left side of the city. The objective is to evaluate the performance of our proposed solution under critical conditions (i.e., congested road). Although we used a high-performance hardware configuration (see the last paragraph in this section), we could not obtain the entire roads

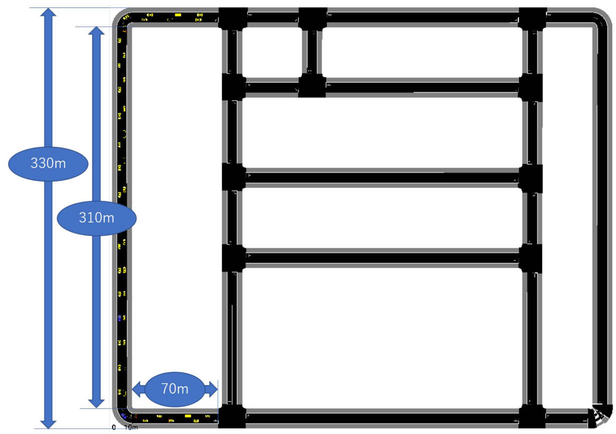

Fig. 4. Road layout of the envisioned scenario.

TABLE I
SUMMARY OF SIMULATION PARAMETERS

Parameter	Values
Protocol stack	ITS-G5
Frequency band	5.9 GHz
Data bitrate	6 Mbit/s
Transmission power	200 mW
Radio propagation model	Free space path loss
CAM DCC profile	DP2
CAM channel type	G5-CCH
T_GenCam	1000 ms
CPM DCC profile	DP2
CPM channel type	G5-CCH
T_GenCpm	100 ms
Camera field of view [°]	40
Camera resolution	1920 × 1080
λ [pixel]	10000
Vehicle identification model accuracy [%]	60, 80, 100
Market penetration rates [%]	10, 40, 70, 100
Vehicle speed	50 km/h
Number of vehicles	45

of the simulated city crowded with vehicles because of the high computation resources required by simulation environments, especially when three simulators are running simultaneously. We summarize the simulation parameters in Table I. According to [43], the minimum and maximum generation intervals for CAM are 100 ms and 1 s, respectively, whereas the default value is 1 s. In our implementation, we generate CAMs every 1 s, provided that heading, position, and velocity do not drastically change. In case of drastic changes, we generate CAMs at shorter intervals, but not less than 100 ms. Our CAM and CPM packet sizes adhere to the ETSI European standards as described in [43]. During the entire simulation time, there are at least 45 simulated vehicles on the road, appearing on one side and disappearing on the other.

For our analysis, we collected data for 5 s, including 2 s of warm-up, from vehicles moving 310 m (i.e., in a straight line), where each simulation step is worth 0.05 s. During warm-up, vehicles start running, exchange CAM and CPM messages with their surroundings to initialize the simulation environment, and record the connected vehicles in their LDMs. It is worth noting that we do not collect measurements during the warm-up phase. As mentioned earlier in this section, evaluating the proposed framework using a higher number of vehicles is not feasible due to hardware limitations. On the other hand, simulating for longer than 5 s will not change the results as the number of vehicles does not change.

In our simulation framework, we use a 3D environment and activate the identification process only when the pixels in the cropped image of the perceived vehicle exceed 10000, unlike previous line-of-sight-based works that use 2D coordinates and draw rectangles to represent vehicles. Furthermore, these works assume that vehicles can be detected even when a tip of the rectangle is visible.

This section focuses on evaluating the proposed approach for vehicle identification and applying it to the CPM redundancy mitigation problem; that is why we simulated the object detection process. Also, we did not consider obstacles (e.g., construction barriers and stop signs) on the road that might slow or even stop vehicles. This is mainly to avoid reducing the frequency of CPM transmission, according to the CPM generation rules mentioned in Section VI-C, leading to a biased analysis. We recall that we assessed the proposed framework using three different model accuracy rates, namely 60 %, 80 %, and 100 %, to account for potential errors related to the detection or classification process. Also, we conducted our simulations with four different MPRs, i.e., the ratio of connected vehicles compared to non-connected ones, corresponding to 10 %, 40 %, 70 %, and 100 %.

The simulation was run on an Ubuntu 18.04 machine, with versions of SUMO, OMNeT++, and Carla simulators of 1.8.0, 5.6.2, and 0.9.10, respectively. Regarding the hardware specifications, we used an Intel i7-10875H CPU, 64 GB of memory, and a GPU NVIDIA GeForce RTX 2070 SUPER (8 GB).

B. Methods of CPM Redundancy Mitigation Used for Comparison

We compared our proposed approach for CPM redundancy mitigation against baseline and ETSI solutions. The baseline solution includes in CPM messages all detected vehicles, every 100 ms, resulting in high situational awareness, but at the cost of increased network traffic (i.e., which may eventually lead to network congestion). We have implemented the ETSI solution in accordance with the CPM generation guidelines described in [15], namely Perceived Object Container Inclusion Management, which reduce the number of objects to be included in CPMs by applying frequency and dynamic filtering. The rest of the graphs (i.e., with prefix V2X- in the figures) consist of three variants from our proposed solution, corresponding to the three different model accuracy rates 60 %, 80 %, and 100 % described previously. A similar method was adopted in prior work [26], but without considering how the perceived vehicle is associated with V2X received messages. Furthermore, in prior work, the vehicle identification has been performed with 100 % accuracy, whereas in our study, different accuracy rates are considered. This will allow us to evaluate the impact of misidentifying some connected vehicles, and eventually do not include them in the CPM messages.

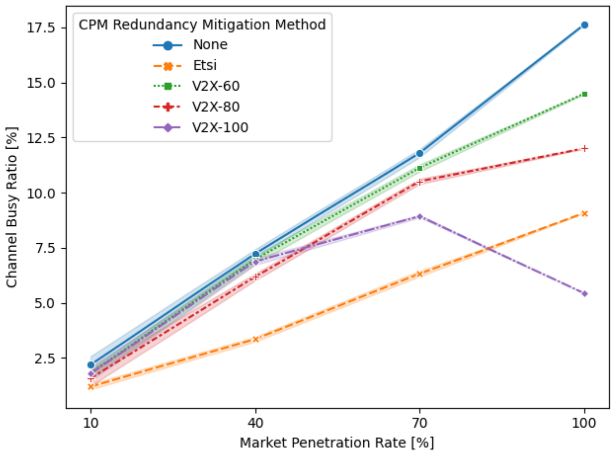

Fig. 5. Performance evaluation in terms of channel busy ratio.

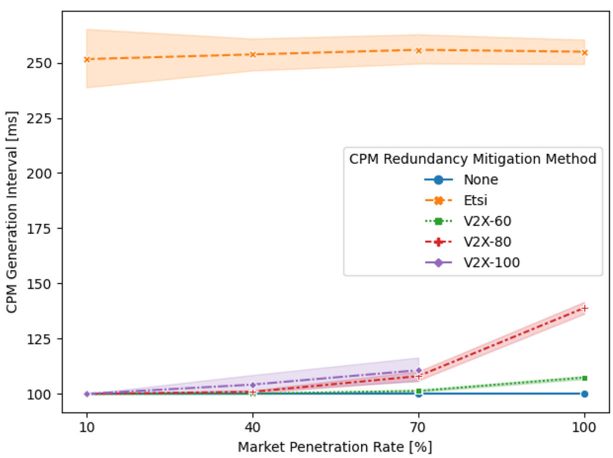

Fig. 6. Performance evaluation in terms of CPM generation frequency.

C. Performance Results

A comparison between the three solutions is driven by two key factors 1) how scrambled the network is, also known as CBR, and 2) how aware a vehicle is of its surroundings within a given range.

Fig. 5 shows a comparison of the CBR between the three solutions. It is readily apparent that the CBR is proportional to the MPR for both baseline and ETSI solutions, but not for our proposed feature-based approach. We conclude from this figure that our proposed solution effectively reduces the network load when both the MPR and the vehicle identification accuracy are high. It requires nearly 100 % identification accuracy and 80 % of MPR to outperform the ETSI method. In this case, the CBR is entirely due to CAMs. ETSI solution, however, performs better in lower- and middle-market penetration scenarios.

Fig. 6 illustrates the comparison between the three solutions from the viewpoint of CPM generation frequency. As seen in this figure, both the baseline solution and our proposed solution always generate CPM messages more frequently than the ETSI solution, which uses an interval of 250 ms because of the vehicle's speed (i.e., at a speed of 50 km/h, the vehicle moves four meters in about 250 ms). As a result, ETSI's CBR rate is lower

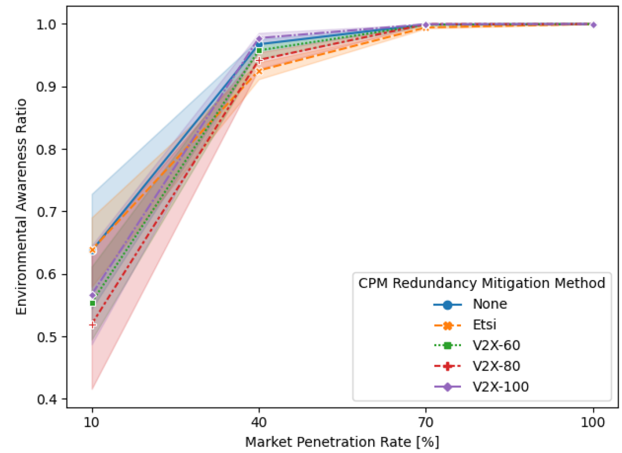

Fig. 7. Performance evaluation in terms of environmental awareness ratio in 100 m range.

than the other solutions, taking into account that the number of detected vehicles is the same for all solutions in our simulations. Please note that frequent CPMs do not always imply higher CBR, as they could be smaller in size. Furthermore, we notice from this figure that the curve of the proposed solution (i.e., V2X-100) starting from 70 % MPR generates no CPMs, which explains the reduced CBR rate in Fig. 5.

Fig. 7 depicts the results regarding the environmental awareness ratio (EAR) within 100 m range. It shows that all solutions achieve high awareness rates, exceeding 90 %, when the MPR is greater than or equal to 40 %. We can also see from this figure that our proposed solution yields the highest awareness rate at medium MPRs, i.e., between 40 % and 70 %, with fewer generated CPM messages, as shown in Fig. 5, in comparison to the baseline solution. By contrast, the ETSI solution exhibits the lowest EAR at the same MPR interval. At low MPRs, our proposed solution manifests the lowest awareness rate, even with 100 % identification accuracy. This demonstrates that our proposed solution is more suitable for environments where medium or all vehicles are connected. It is worthwhile mentioning that the EAR considers vehicles detected by local sensors and received via CAM or CPM messages.

VII. Conclusion

Many ITS applications rely on vehicle identification functionality in order to operate properly. This paper proposes a feature-based vehicle identification method for identifying connected vehicles based on their visible features. The proposed method combines V2X data, exchanged via CAM or CPM messages, with locally sensed data, using onboard sensors, to eventually extract the Communication ID of the perceived vehicles. To assess the efficiency of the proposed method, we applied it to the CPM redundancy mitigation problem, which addresses both the size and frequency of CPMs. In addition, we created a simulation framework, dubbed CARTERY, that integrates three different simulators - SUMO, Carla, and OMNeT++, to be able to evaluate our proposed solution and compare it against the baseline and ETSI solutions. The obtained results reveal that the ETSI method effectively reduces CPMs when the number of connected vehicles is relatively small; however, it also reduces the environmental awareness of the vehicles. On the other hand, V2X feature-based vehicle identification, with 100 % accuracy, exhibits a better tradeoff between the network load and the environmental awareness rate compared to both baseline and ETSI methods, especially at high market penetration rates (80 % and above).

As part of future research, we plan to improve the proposed solution to keep up with the growing number of non-connected vehicles on the roads. We also intend to assess the processing time of vehicle identification in the simulated environment, even though the delay does not affect the simulation results presented in this paper because the data association depends mainly on the vehicle's appearance. Lastly, taking obstacle shadowing into account when calculating the radio power could be another interesting subject for further study.

References

[1] S. Iranmanesh, F. S. Abkenar, A. Jamalipour, and R. Raad, "A heuristic distributed scheme to detect falsification of mobility patterns in internet of vehicles," *IEEE Internet Things J.*, vol. 9, no. 1, pp. 719–727, Jan. 2022.

[2] O. E. Marai and T. Taleb, "Smooth and low latency video streaming for autonomous cars during handover," *IEEE Netw.*, vol. 34, no. 6, pp. 302–309, Nov./Dec. 2020.

[3] T. Taleb, A. Ksentini, and F. Filali, "Wireless connection steering for vehicles," in *Proc. IEEE Glob. Commun. Conf.*, 2012, pp. 56–60.

[4] T. Taleb, A. Benslimane, and K. B. Letaief, "Toward an effective risk-conscious and collaborative vehicular collision avoidance system," *IEEE Trans. Veh. Technol.*, vol. 59, no. 3, pp. 1474–1486, Mar. 2010.

[5] M. Fisher, L. Dennis, and M. Webster, "Verifying autonomous systems," *Commun. ACM*, vol. 56, no. 9, pp. 84–93, Sep. 2013. [Online]. Available: https://doi.org/10.1145/2494558

[6] N. Chaib, O. S. Oubbati, M. L. Bensaad, A. Lakas, P. Lorenz, and A. Jamalipour, "BRT: Bus-based routing technique in urban vehicular networks," *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 11, pp. 4550–4562, Nov. 2020.

[7] M. Z. Alam, F. S. Abkenar, I. Adhicandra, S. Murali, and A. Jamalipour, "Low-delay path selection for cluster-based buffer-aided vehicular communications," *IEEE Trans. Veh. Technol.*, vol. 69, no. 9, pp. 9356–9363, Sep. 2020.

[8] Y. Yuan, G. Zheng, K.-K. Wong, and K. B. Letaief, "Meta-reinforcement learning based resource allocation for dynamic V2X communications," *IEEE Trans. Veh. Technol.*, vol. 70, no. 9, pp. 8964–8977, Sep. 2021.

[9] M. Z. Alam, I. Adhicandra, K. S. Khan, and A. Jamalipour, "SDP-IGD: An iterative power allocation technique for cluster-based multihop vehicular communications," *IEEE Trans. Veh. Technol.*, vol. 69, no. 7, pp. 7908–7915, Jul. 2020.

[10] W. Qi, Q. Li, Q. Song, L. Guo, and A. Jamalipour, "Extensive edge intelligence for future vehicular networks in 6G," *IEEE Wireless Commun.*, vol. 28, no. 4, pp. 128–135, Aug. 2021.

[11] ETSI, "Intelligent transport systems (ITS); Vehicular communications; Basic set of applications; Part 2: Specification of cooperative awareness basic service," ETSI, Sophia Antipolis, France, Tech. Rep. EN 302 637-2-V1.3.1, 2017.

[12] ETSI, "Intelligent transport systems (ITS); Vehicular communications; Basic set of applications; Analysis of the collective perception service (CPS); Release 2," ETSI, Sophia Antipolis, France, Tech. Rep. 103 562-V2.1.1, 2019.

[13] G. Thandavarayan, M. Sepulcre, and J. Gozalvez, "Generation of cooperative perception messages for connected and automated vehicles," *IEEE Trans. Veh. Technol.*, vol. 69, no. 12, pp. 16336–16341, Dec. 2020.

[14] I. The technology consulting firm Gartner, "Gartner says 5.8 billion enterprise and automotive IoT endpoints will be in use in 2020," 2019. Accessed: Jun. 8, 2021. [Online]. Available: https://www.gartner.com/en/newsroom/press-releases/2019-08-29-gartner-says-5-8-billion-enterprise-and-automotive-io

[15] ETSI, "Intelligent transport systems (ITS); Vehicular communications; basic set of applications; analysis of the collective perception service (CPS); Release 2," 2019. Accessed: Nov. 8, 2021. [Online]. Available: https://www.etsi.org/deliver/etsi_tr/103500_103599/103562/02.01.01_60/tr_103562v020101p.pdf

[16] A. Fujita, H. Yamaguchi, T. Higashino, and M. Takai, "Detection relative position of vehicles by sharing information of laser range scanner through V2V communication," in *Proc. 24th DPS Workshop*, 2016, vol. 2016, pp. 31–39.

[17] Z. Chen and B. B. Park, "Preceding vehicle identification for cooperative adaptive cruise control platoon forming," *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 1, pp. 308–320, Jan. 2020.

[18] F. de Ponte Müller, "Survey on ranging sensors and cooperative techniques for relative positioning of vehicles," *Sensors*, vol. 17, no. 2, 2017, Art. no. 271.

[19] H. H. Meinel, "Evolving automotive radar – From the very beginnings into the future," in *Proc. 8th Eur. Conf. Antennas Propag.*, 2014, pp. 3107–3114.

[20] K. Abboud, H. A. Omar, and W. Zhuang, "Interworking of DSRC and cellular network technologies for V2X communications: A survey," *IEEE Trans. Veh. Technol.*, vol. 65, no. 12, pp. 9457–9470, Dec. 2016.

[21] W. Qi, B. Landfeldt, Q. Song, L. Guo, and A. Jamalipour, "Traffic differentiated clustering routing in DSRC and C-V2X hybrid vehicular networks," *IEEE Trans. Veh. Technol.*, vol. 69, no. 7, pp. 7723–7734, Jul. 2020.

[22] H. Masuda, M. Tsukada, and H. Esaki, "Integrating sensor data and shared data using license plate for data integration," in *Proc. Multimedia, Distributed, Cooperative, Mobile Symp.*, 2020, pp. 1094–1101.

[23] ETSI, "Intelligent transport systems (ITS); Vehicular communications; GeoNetworking; Part 4: Geographical addressing and forwarding for point-to-point and point-to-multipoint communications; Sub-part 1: Media-Independent functionality," ETSI, Sophia Antipolis, France, Tech. Rep. EN 302 636-4-1-V1.2.1, 2014.

[24] ETSI, "Intelligent transport systems (ITS); Vehicular communications; GeoNetworking; Part 5: Transport protocols; Sub-part 1: Basic transport protocol," ETSI, Sophia Antipolis, France, Tech, Rep. EN 302 636-5-1-V2.1.0, 2017.

[25] K. Garlichs, H.-J. Gunther, and L. C. Wolf, "Generation rules for the collective perception service," in *Proc. IEEE Veh. Netw. Conf.*, 2019, pp. 1–8.

[26] Q. Delooz and A. Festag, "Network load adaptation for collective perception in V2X communications," in *Proc. IEEE Int. Conf. Connected Veh. Expo*, 2019, pp. 1–6.

[27] F. Mütsch, "TalkyCars: A distributed software platform for cooperative perception among connected autonomous vehicles based on Cellular-V2X communication," M.S. thesis, Karlsruhe Inst. Technol., Germany, 2020.

[28] S. Aoki, T. Higuchi, and O. Altintas, "Cooperative perception with deep reinforcement learning for connected vehicles," in *Proc. IEEE Intell. Veh. Symp.*, 2020, pp. 328–334.

[29] T. Lee et al., "Building a V2X simulation framework for future autonomous driving," in *Proc. 20th Asia-Pacific Netw. Operations Manage. Symp.*, 2019, pp. 1–6.

[30] C. Olaverri-Monreal, J. Errea-Moreno, A. Díaz-Álvarez, C. Biurrun-Quel, L. Serrano-Arriezu, and M. Kuba, "Connection of the SUMO microscopic traffic simulator and the unity 3D game engine to evaluate V2X Communication-Based systems," *Sensors*, vol. 18, no. 12, Dec. 2018, Art. no. 4399.

[31] D. Jia, J. Sun, A. Sharma, Z. Zheng, and B. Liu, "Integrated simulation platform for conventional, connected and automated driving: A design from cyber–physical systems perspective," *Transp. Res. Part C: Emerg. Technol.*, vol. 124, 2021, Art. no. 102984. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0968090X2100019X

[32] D. C. Selvaraj, "Development of a framework for sensor- and communication-assisted vehicle dynamic," M.S. thesis, Politecnico di Torino, Italy, Mar. 2020.

[33] M. Randriamasy, A. Cabani, H. Chafouk, and G. Fremont, "Geolocation process to perform the electronic toll collection using the ITS-G5 technology," *IEEE Trans. Veh. Technol.*, vol. 68, no. 9, pp. 8570–8582, Sep. 2019.

[34] S. Shivshankar and A. Jamalipour, "An evolutionary game theory-based approach to cooperation in VANETs under different network conditions," *IEEE Trans. Veh. Technol.*, vol. 64, no. 5, pp. 2015–2022, May 2015.

[35] R. Deng, B. Di, and L. Song, "Cooperative collision avoidance for overtaking maneuvers in cellular v2x-based autonomous driving," *IEEE Trans. Veh. Technol.*, vol. 68, no. 5, pp. 4434–4446, May 2019.

[36] S. B. Prathiba, G. Raja, and N. Kumar, “Intelligent cooperative collision avoidance at overtaking and lane changing maneuver in 6G-V2X communications,” *IEEE Trans. Veh. Technol.*, vol. 71, no. 1, pp. 112–122, Jan. 2022.
[37] A. Dosovitskiy, G. Ros, F. Codevilla, A. Lopez, and V. Koltun, “CARLA: An open urban driving simulator,” in *Proc. 1st Annu. Conf. Robot Learn.*, 2017, pp. 1–16.
[38] R. Riebl, H. Günther, C. Facchi, and L. Wolf, “Artery: Extending veins for VANET applications,” in *Proc. Int. Conf. Models Technol. Intell. Transp. Syst.*, 2015, pp. 450–456.
[39] ETSI, “Intelligent transport systems (ITS); Communications architecture,” ETSI Sophia Antipolis, France, Tech. Rep. EN 302 665 - V1.1.1, 2010.
[40] A. Varga and R. Hornig, “An overview of the OMNeT++ simulation environment,” in *Proc. 1st Int. Conf. Simul. Tools Techn. Commun., Netw. Syst. Workshops*, 2008, pp. 1–10.
[41] P. A. Lopez et al., “Microscopic traffic simulation using SUMO,” in *Proc. 21st IEEE Int. Conf. Intell. Transp. Syst.*, 2018, pp. 2575–2582. [Online]. Available: https://elib.dlr.de/124092/
[42] R. Riebl, C. Obermaier, S. Neumeier, and C. Facchi, “Vanetza: Boosting research on inter-vehicle communication,” in *Proc. 5th GI/ITG KuVS Fachgespräch Inter- Veh. Commun.*, 2017, pp. 37–40.
[43] ETSI, “Intelligent transport systems (ITS); Vehicular communications; Basic set of applications; Part 2: Specification of cooperative awareness basic service,” 2014. Accessed: Nov. 8, 2021. [Online]. Available: https://www.etsi.org/deliver/etsi_en/302600_302699/30263702/01.03.01_30/en_30263702v010301v.pdf

Hidetaka Masuda received the Bachelor of Engineering degree and the Master of Information Science and Engineering degree from the University of Tokyo, Tokyo, Japan, in 2019 and 2021, respectively. He was a Research Assistant with Aalto University, Espoo, Finland, from September 2020 to December 2020. His research focuses on intelligent transport systems.

Oussama El Marai received the Engineering degree in computer science from the University of Science and Technology Houari Boumediene, Algiers, Algeria, in 2005, and the master’s degree from Ecole Nationale Superieure d’Informatique, Algeria, in 2009. He is currently working toward the Doctoral degree with the School of Electrical Engineering, Aalto University, Espoo, Finland. His research interests include adaptive video delivery, user QoE optimization, digital twin, image processing, vehicular technology, and intelligent transportation systems.

Manabu Tsukada received the B.S. and M.S. degrees from Keio University, Minato, Japan, in 2005 and 2007, respectively, and the Ph.D. degree from the Centre de Robotique, Mines ParisTech, Paris, France, in 2011. He is currently an Associate Professor with the Graduate School of Information Science and Technology, the University of Tokyo, Tokyo, Japan. He is also a designated Associate Professor with the Center for Embedded Computing Systems, Nagoya University, Nagoya, Japan. He is currently a Visiting Professor with Aalto University, Espoo, Finland, from February 2021 to November 2021. He was with IMARA Team, Inria, France, during his Ph.D. degree. During his pre and postdoc research stages, he has participated in a multitude of international projects in the networked ITS area, such as GeoNet, ITSSv6, SCORE@F, CVIS, Nautilus6, or ANEMONE. His research interests include mobility support for the next-generation Internet (IPv6), Internet audio-visual media, and communications for intelligent vehicles. He has been serving as a Board Member of the WIDE Project since 2014.

Tarik Taleb (Senior Member, IEEE) received the B.E degree in information engineering with distinction and the M.Sc. and Ph.D. degrees in information sciences from Tohoku University, Sendai, Japan, in 2001, 2003, and 2005, respectively. He is currently a Professor with the Centre for Wireless Communications (CWC) – Networks and Systems Unit, Faculty of Information Technology and Electrical Engineering, The University of Oulu, Oulu, Finland. He is the founder and the Director of the MOSA!C Lab. Between October 2014 and December 2021, he was a Professor with the School of Electrical Engineering, Aalto University, Espoo, Finland. Prior to that, he was a Senior Researcher and 3GPP Standards Expert at NEC Europe Ltd, Heidelberg, Germany. Before joining NEC and till March 2009, he was an Assistant Professor with the Graduate School of Information Sciences, Tohoku University, in a lab fully funded by KDDI, the second largest mobile operator in Japan. From October 2005 till March 2006, he was a Research Fellow with the Intelligent Cosmos Research Institute, Sendai, Japan. His research interests include telco cloud, network softwarization & network slicing, AI-based software defined security, immersive communications, mobile multimedia streaming, & next generation mobile networking. Prof. Taleb has been also directly engaged in the development and standardization of the Evolved Packet System as a Member of 3GPP’s System Architecture working group two. Prof. Taleb was the General Chair of the 2019 edition of the IEEE Wireless Communications and Networking Conference (WCNC’19) held in Marrakech, Morocco. He was the Guest Editor in Chief of the IEEE JSAC Series on Network Softwarization & Enablers. He was on the Editorial Board of the IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS, *IEEE Wireless Communications Magazine*, IEEE JOURNAL ON INTERNET OF THINGS, IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY, IEEE COMMUNICATIONS SURVEYS & TUTORIALS, and a number of Wiley journals. Till Decmber 2016, he was the Chair of the Wireless Communications Technical Committee, the largest in IEEE ComSoC. He also was the Vice Chair of the Satellite and Space Communications Technical Committee of IEEE ComSoc (2006–2010). Prof. Taleb was the recipient of the 2021 IEEE ComSoc Wireless Communications Technical Committee Recognition Award (December 2021), the 2017 IEEE ComSoc Communications Software Technical Achievement Award (December 2017) for his outstanding contributions to network softwarization. He is also the corecipient of the 2017 IEEE Communications Society Fred W. Ellersick Prize (May 2017), 2009 IEEE ComSoc Asia-Pacific Best Young Researcher award (June 2009), 2008 TELECOM System Technology Award from the Telecommunications Advancement Foundation (March 2008), 2007 Funai Foundation Science Promotion Award (April 2007), 2006 IEEE Computer Society Japan Chapter Young Author Award (December 2006), Niwa Yasujirou Memorial Award (February 2005), and the Young Researcher’s Encouragement Award from the Japan chapter of the IEEE Vehicular Technology Society (VTS) (October 2003). Some of Prof. Taleb’s research work was the recipient of the best paper awards at prestigious IEEE-flagged conferences.

Hiroshi Esaki (Member, IEEE) is currently a Professor with the Graduate School of Information Science and Technology, University of Tokyo, Bunkyo, Japan. In 1987, he joined Research and Development Center, Toshiba Corporation, where he engaged in the research of ATM systems. From 1990 to 1991, he has been with Bellcore Inc., New Jersey, USA, as a residential Researcher. From 1994 to 1996, he has been with Columbia University, New York, NY, USA. He has proposed the CSR architecture that is one of the origin of MPLS (Multi-Protocol Label Switching), to the IETF and to the ATM Forum. From 1998, he was a Professor with the University of Tokyo, and a Board Member of WIDE Project. From 1997, he has involved in many of the IPv6 research and development at the WIDE project. He is a cofounder of series of IPv6 special project in the WIDE project, (KAME Project, TAHI Project USAGI Project). He is an Executive Director of IPv6 promotion council, the Vice Chair of JPNIC (Japan Network Information Center), and the Chair of IPv6 Ready Logo Program run by IPv6 Forum.