SAFER Pre-studies

Final Report

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Project Title	Cooperative Automated Driving Use Cases for V2X Communication
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Contents

Summary

One of the main challenges today on the way towards full traffic automation is the comprehensive environmental perception of its participants, which in turn can help to improve the safety and assistance in applications such as Advanced Driver Assistance Systems. In order to be able to assist the driver or even take decisions themselves, vehicles have to perceive their surroundings and detect possible dangers and hazards as precisely as possible. Most of the sensor systems often fall short when meeting the strict functional requirements imposed by such systems. Vehicle-to-Everything communication has emerged as a promising technology to mitigate this gap, allowing traffic participants to share information that help to increase their environmental perception and support their decision-making basis. Examples of Vehicle-to-Everything applications are cooperative awareness, collaborative positioning, and collective perception, allowing vehicles to share data about their own state, detected objects in their surroundings, among others.

With this in mind, this pre-study aims to answer the following central research question: *What are the latency requirements for collective perception systems to enable Advanced Driver Assistance Systems function to fulfil the state-of-the-art safety norms in a realistic traffic use case?* With the goal of solving the above question, the pre-study focusses on establishing a tool chain data-scenarios-simulation-requirements that help us to understand the needed pieces/shortcomings of the data and tools. Such a study would enable to set the requirement on latency of Vehicle-to-Everything communication systems based on safety requirement of Advanced Driver Assistance Systems functions. Halmstad University is the responsible for the pre-study and the co-production involve two parties, namely Viscando AB and Zenseact AB, that are interested on the achievement of the present pre-study.

Cooperative Automated Driving Use Cases for V2X Communication

1. Background

Advanced Driver Assistance Systems (ADAS) and Autonomous Driving (AD) are progressing towards higher speeds and more complex dynamic scenarios, where the on-board sensor systems may not be sufficient to provide adequate awareness of traffic situation for accurate and timely situation assessment and action. That is why the connected vehicles technologies, such as vehicle-to-everything (V2X) communication, are receiving attention as enabling sharing the accurate position information between vehicles. As the share of V2X equipped vehicles is currently too small, stationary V2X equipped traffic sensors are a promising solution, as these can detect and share the information about all objects present in a specific road section. Particularly, cooperative perception, also known as collective perception, realized by fusing the object data sensed by the on-board sensors with information received from the infrastructure sensors, has potential to bring together driving automation technology with V2X communication. However, cooperative perception is heavily dependent on the timeliness of the data received by a connected vehicle. Thus, one of the great challenges is to study how the latency affects the performance of the AD or ADAS functionalities in dealing with safety critical traffic cases.

Existing literature have been focusing on investigating the factors involved in cooperative perception systems. To this date, there are limited options regarding the technologies that can enable direct V2X communications. Among one of the available and standardized options is the Wi-Fi based IEEE 802.11p standard, also known as Dedicated Short-Range Communication (DSRC) in USA and ITS-G5 in Europe. The second cellular-based technology, known as C-V2X, has recently been proposed as possible enabler of direct V2X communications by the 3rd Generation Partnership Project (3GPP) using the sidelink or PC5 interface (3rd Generation Partnership Project, 2017). Yet, a final decision on which technology should be used regarding V2X communication is still pending.

2. Project set up

2.1 Purpose

The present pre-study is fully aligned with the SAFER's vision, especially with its primary goal of bringing people together to create research that enable safe mobility for people and goods. The last was done in the sense that the core of the pre-study focus on the study of realistic scenarios where cooperative perception enable vehicles to coordinate their

driving maneuvers and achieve a common knowledge of their surroundings, leading to a safer and more efficient driving.

2.2 Objectives

As mentioned before, cooperative perception is still in a state of research and therefore, state-of-the-art collective perception often fall short when meeting the functional requirements of the sensor systems imposed by the applications. Whit that in mind, the research question addressed in this pre-study is: *determine the latency requirements for collective perception systems to enable AD/ADAS function to fulfil the state-of-the-art safety norms in a realistic traffic use case*. Based on the purpose and research question of the present pre-study, the following objectives were proposed:

2.2.1 Establish a tool chain data-scenarios-simulation-requirement.
2.2.2 Understand the needed pieces/shortcomings of the data and tools.
2.2.3 Apply for a larger project to continue building the framework.

2.3 Project period

The present pre-study was carried out in the period May – June 2021

2.4 Partners

The co-production involved parties that are interested on the findings and deliverables from the present pre-study. Viscando AB has an interest in understanding large amount of complex traffic data as well as understanding the use cases and requirements for using their stationary sensors in V2X collective perception systems. Zenseact AB is interested in understanding user behavior and traffic dynamics on merging scenarios for the development of connected vehicles' functionalities. In addition, the co-production can ensure potential benefits to the companies since both are willing to investigate the traffic dynamics and the potential of V2X for ensuring safe merging in the identified scenarios. It is important to highlight that the co-production also involved an iterative process between all parties with the aim of reaching the objectives described in this pre-study.

3. Method and Activities

To approach the research question and the derived objectives, our methodology was fundamentally based on the following performed activities:

3.1 Reviewing the application of V2X communication in collective perception systems

Understanding the data which needs to be communicated from infrastructure to CAV to enable safe driving is of great importance for enabling safe mobility. These systems will allow improvements in safety, but also in the performance, efficiency, and environmental impact of transportation. Thus, it is crucial to think about this cooperative element. In many aspects today's vehicles are already connected devices and, in the very near future they will also interact directly with each other and with the road infrastructure. Thus, it

is important to identify and formulate requirements for maximum uncertainties in parameters estimation achieved by the camera-based system (e.g., speed and acceleration) as well as for overall latencies from the moment of retrieving theses parameters until they should be communicated to CAVs. A revision of the literature was done with the aim to find out the gaps and challenges in this matter.

3.2 Collecting the data on the interactions between cars and unprotected road users using already installed Viscando stationary 3D and AI-based sensors.

One of the expected results is to identify what the unexpected and repeated events looks like and understand the needed pieces of the data. For doing that, we analyzed a data set consisting of trajectories of vehicles, cyclists, and pedestrians at Lindholmen intersection in Göteborg, shown in Figure 1. Every data point consists of a timestamp, position in x- and y- coordinates, speed, type of road user and an identification number (ID). Each ID represents a unique subset of data points corresponding to each road user. The origin and scale are given for the x- and y- coordinates. Moreover, every road user is tracked at its center of mass and all tracking is relative to the ground. The data has a sampling frequency of 20 Hz and was recorded consecutively during an entire day.

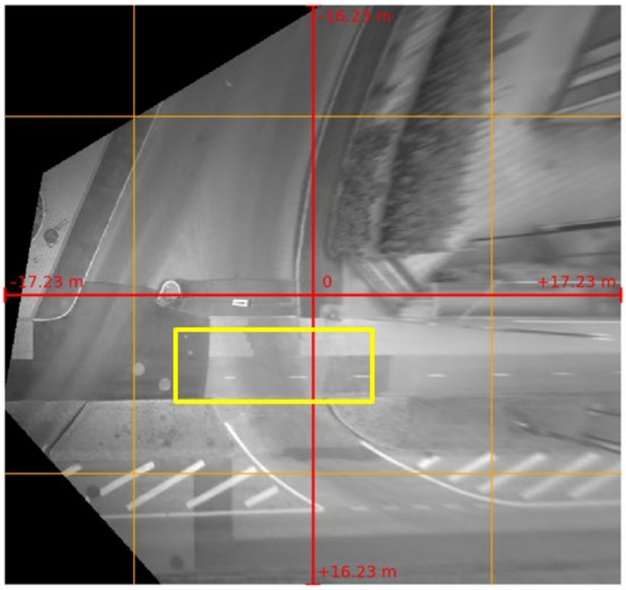

Figure 1 Lindhorlmen intersection in Göteborg.

3.3 Identifying different scenarios from the data collected with the Viscando sensors.

From the raw data we created a structure that facilitated our search for edge-cases scenarios and near crash situations. Accordingly, we measured the closeness of a collision.

We applied Post Encroachment Time (PET) to measure how close an interaction between two agents, passing each other at right angles in an intersection, was to a collision.

Algorithm 1 describes how PET was calculated. First, all points that were not part of the selected area were removed. Next, the agents corresponding to those points were excluded. PETs were calculated for the remaining road users if their first recorded time in the filtered data differed by a threshold time of $t_{threshold} = 30$ s. Once the data was filtered, the closest positions between each vehicle and pedestrian / cyclist were found. Following, the PET for each vehicle and pedestrian / cyclist was calculated by taking the difference of the recorded times at the closest positions. Moreover, if the distance between the closest positions were greater than 0.3 m, then the PET value was excluded since the actual intersection was assumed to happen outside the selected area.

Algorithm 1 Calculation of Post Encroachment Times

Remove data points that are not part of the selected area
Remove agents that are part of the excluded data points
Let $V = \{Remaining\ vehicles\}$ and $A = \{Remaining\ pedestriants\ and\ cyclists\}$
for $v \in V$ **do**
    for $a \in A$ **do**
        if $|t_{start}(v) - t_{start}(a)| < t_{threshold}$ **then**
            Find closest observed positions p_v and p_a between vehicle v and agent a
            if $|p_v - p_a| < 0.3$ **then**
                $\mathrm{PET}[v, a] = |t(p_s) - t(p_a)|$
            end if
        end if
    end for
end for

Once we calculated the PETs, the critical scenarios were selected. The scenarios were categorized following Table 1. Accordingly, only the scenarios considered as serious conflict were simulated.

Table 1 Thresholds of PETs

PET/s	Traffic conflict level
0 – 2	*Serious*
2.01 – 4.01	*General*
4.02 – 6.02	*Slight*
> 6.02	*Potential*

3.4 Simulating the identified scenarios using the MATLAB Automated Driving Toolbox.

The MATLAB/Simulink® environment with available simple reference applications for collision avoidance was used. MATLAB/Simulink® enables users to analyze data, design algorithms, and generate models and is typically used in the automotive industry because

supporting Model-Based Development. Moreover, MATLAB/Simulink® includes the Automated Driving Toolbox (ATD) to support the self-driving systems. ADT provides algorithms and tools for designing, simulating, and testing self-driving systems, including Driving Scenario Designer (DSD) app, which enables users to design synthetic driving scenarios for testing autonomous driving systems. DSD can create roads, actor models, configure vision, and attach sensors such as light detection and ranging (LiDAR) to the vehicles sensors and use these sensors to generate actor and boundary detections, point cloud data, and inertial measurements. The main goal is to simulate the scenarios considered as near to crash situations. From the previous step, we could identify such scenarios and identified the ID agents and corresponding data points, by doing so, we could extract the data and use it as input to our simulator.

4. Results and Deliverables

The pre-study findings support a theoretical basis for a variety of comprehensive intelligent transportation systems, in particular, V2X cooperation systems. Thus, the deliverables from this pre-study can be summarized as follows:

- Understanding of the current collective perception state-of-the-art.
- Questions and challenges regarding the latency requirements for collective perception systems.
- Simulation of the identified conflict scenarios with an Open-Loop model using Automated Driving Toolbox from MATLAB/Simulink®.
- Establishing of a partnership among industry actors with interest in the field.
- Submission of a conference paper generated during the development of the present pre-study.

4.1 Literature Review

Reliable V2X communications are the critical component of connected vehicle technology applications. One of the great challenges is the development of V2X communication protocols, which would be able to support a variety of different use-cases, scenarios, and autonomy levels. In this pre-study we focus on infrastructure to CAVs communication to mitigate safety concerns and to enable comfort and efficient movement on intersections.

On this matter, recent studies have considered the inclusion of V2X characteristics when modelling driver behaviors. (Wang, Wu, & Barth, 2018) proposed a protocol for the highway on-ramp merging system and made some assumptions while modelling the system. The authors proposed a system that takes advantage of V2X communications assuming that all vehicles in the study were CAVs with the ability to communicate between each other using vehicle-to-vehicle (V2V) communications, and with the infrastructure using vehicle-to-infrastructure (V2I) communications. As for the V2V, they assumed that CAVs can obtain their own information from appropriate sensors and share them with other CAVs in the Vehicular Ad-Hoc Network through DSRC. As for the V2I

communications, they assumed that CAVs can share their information with Restricted Short Units-equipped infrastructure, while those infrastructures can in turn share Geographic Information System and Sequence Identification with CAVs through DSRC. The proposed protocol was designed to arrange vehicles with a predefined sequence, so they can cooperate with each other before merging. Authors tested the proposed system by using the microscopic traffic simulator VISSIM, in particular, authors built the simulation based on the on-ramp from University of California, Riverside County campus area.

More recently, (Nassef, Sequeira, Salam, & Mahmoodi, 2020) proposed a coordination model based on reinforcement learning for a scenario where a vehicle is merging into a carriageway between two vehicles. The NGSIM dataset was used for training, testing, and validating the proposed model. The proposed model was compared against state-of-the-art machine learning prediction algorithms to provide some insights of the expected accuracy. Moreover, to facilitate the lane merge coordination, bespoke trajectories recommendations were determined and sent by central coordination mechanism to connected vehicles through an edge cloud approach composed by: a V2X gateway, and image recognition system, a global dynamic map, a data fusion model and a traffic orchestrator model.

Although studies have focused on make use of V2X communication, minimum effort has been made for analyzing the latency requirements of well-known vehicle safety applications of highway, such as ADAS or cooperative Adaptive Cruise Control. (Schiegg, Bischoff, Krost, & Llatser, 2020) presented an analytical model that allows estimating the absolute and the relative number of objects contained in both Local Environmental Model (LEM) and Global Environmental Model (GEM), in dependence of macroscopic parameters, such as the linear vehicle density and the properties of road, vehicles and sensors. (Du, o.a., 2019) inspired by the drawback of the software simulators for simulating scenarios in V2X applications, presented a testing system based on cooperative system technology which introduces the cooperative positioning structure and network model. However, state-of-the-art collective perception often fall short when meeting the functional requirements of the sensor systems imposed by the applications.

Recently, (Schiegg, Brahmi, & Llatser, 2019) investigated the performance of V2X application, collective perception, within networks based on IEEE 802.11p technology. The authors considered what they called measurement delay dominated by the update rate of the sensor system, including the necessary processing time before its integration into the LEM, as a major metric to measure the performance of collective perception. For the evaluation, authors considered that vehicles' updated rate was set to 50 *ms*, which is a typical value for this kind of sensor systems, however, this assumption is often ambitious since cooperative perception is still in a state of research.

Although the research efforts studied to date have tried to enhance the understanding of coordination of CAVs, some open issues to be addressed were found. One of the questions that arises is regarding the performance of V2X applications, such as cooperative

perception: *"what are the safety requirements on real-world scenarios that vehicles with advanced driver assistance functionalities would need to manage?"*. To the best of our knowledge, V2X communications are promising when talking about reducing traffic accidents and easing congestion by enabling vehicles to give a rapid response for changes in their mutual environment. Thus, another question is related to the infrastructure and the actual environment as it is with tons of data from vehicle and infrastructure: *"how can CAV handle interventions from human-driven traffic merging/exiting highway with the assistance V2X-enabled traffic-camera system?"*. This is likely to understand the data which needs to be communicated from infrastructure to CAV to enable safe driving. Formulate requirements for maximum uncertainties in parameters estimation achieved by camera-based system as well as for overall latency from the moment of retrieving these parameters until they should be communicated to CAV is of great importance.

4.2 Implementing the Concept of Post-Encroachment Time (PET)

PET calculations can provide some help to the traffic safety evaluation or traffic collision prediction under connected vehicle environment. Based on the activities done, as cited in subsection 3.3, 385 PET values were calculated. Then, using 2 as the grouping length, the PET data were divided into 4 groups. The grouping results are presented in Table 2.

Table 2 PET data chart.

PET/s	Number
0 – 2	*5*
2.01 – 4.01	*104*
4.02 – 6.02	*70*
> 6.02	*206*

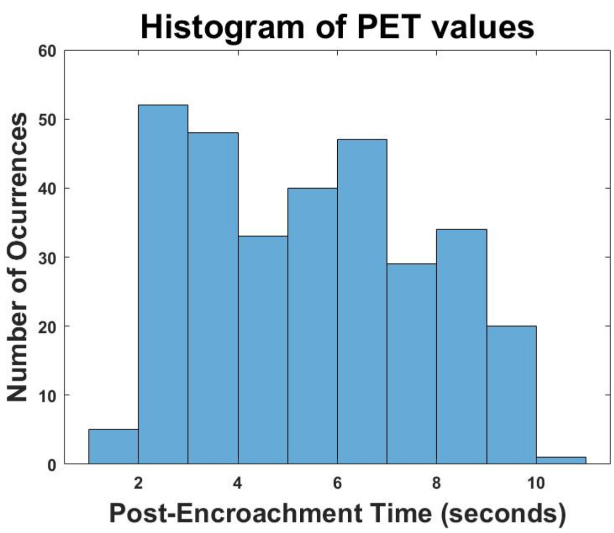

Figure 2 Histogram of the PET values less than 10 s.

Figure 2 presents histogram of the PET values less than 10 s for possible conflicts between either pedestrians and vehicles or cyclists and vehicles. Figure 3 presents values where the cyclist or pedestrian was the first actor to arrive at the intersection of the trajectories. Furthermore, Figure 4 depicts values where the vehicle was the first actor arriving at the intersection.

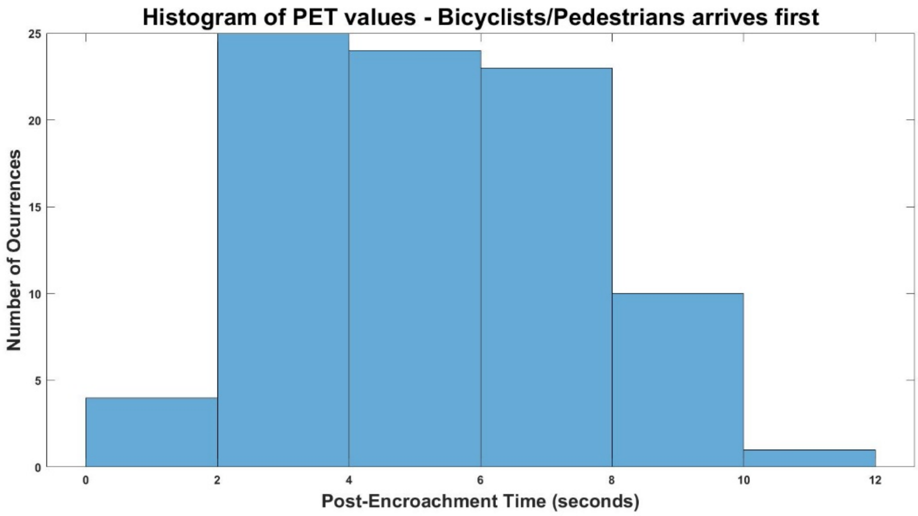

Figure 3 Cyclist/Pedestrians as first actor to arrive first.

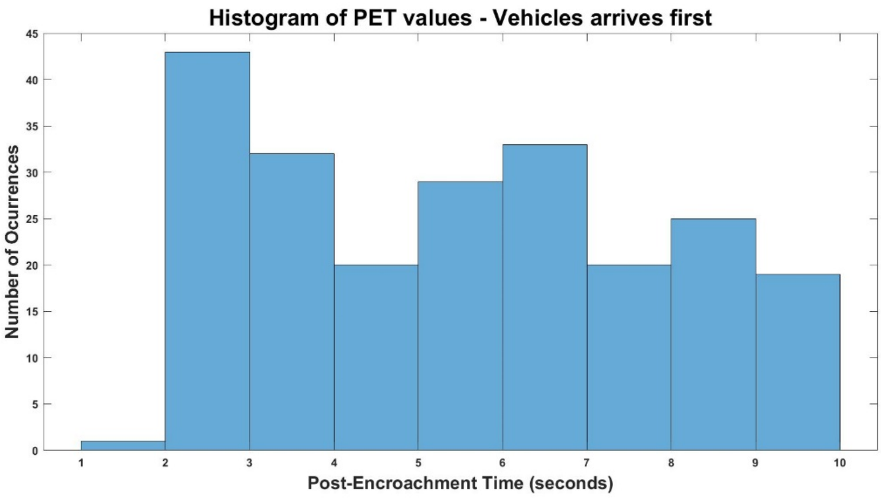

Figure 4 Vehicle as first actor to arrive first.

Statistical analysis results showed that variability of the PET values can be well described by a 2-parameter Weibull distribution, as seen in Figure 5, with a scale parameter of $\alpha = 7.9354$ and a shape parameter of $\beta = 1.8845$, whose basic probability density function is given by Equation 1. The Weibull distribution is one of the most commonly used distributions in reliability engineering because of the many shapes it attains for various values of β (slope). It can therefore be used for modelling a great variety of data and life

characteristics, for example, it has been adopted in modelling breakdown probability at bottlenecks on expressways (Brilon, Geistefeldt, & Zurlinden, 2007).

$$f(x,\ \alpha, \beta) = \frac{\beta}{\alpha}\left(\frac{x}{\alpha}\right)^{\beta-1} e^{-(x/\alpha)^{\beta}}$$

Equation 1

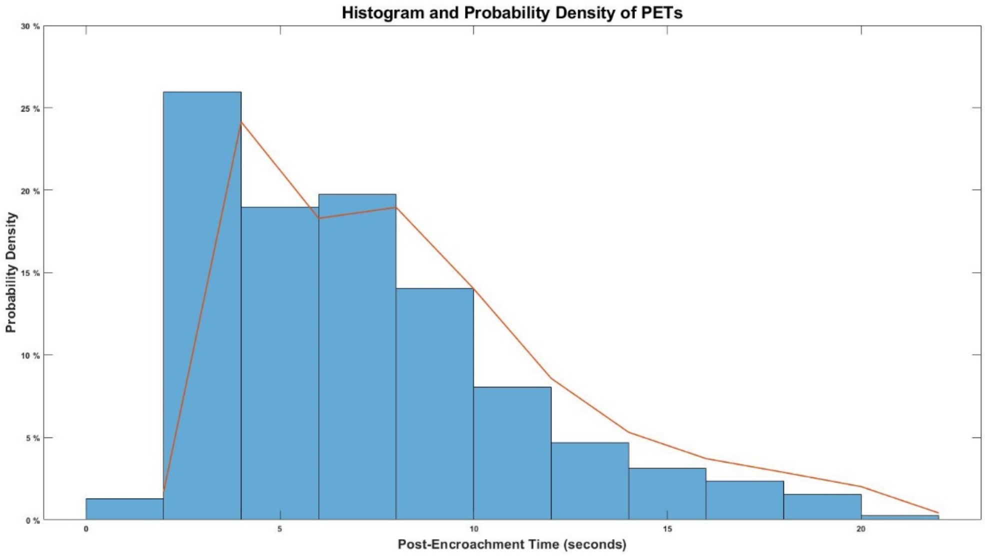

Figure 5 Histogram and probability of all PET data.

4.3 Implementing Open-Loop ADAS Algorithm using Driving Scenario

As mentioned in subsection 3.4, we used MATLAB/Simulink® to simulate the identified scenarios using the Open-Loop models. First, a driving scenario is created using the DSD. The `drivingScenario` object represents a 3-D arena containing roads, vehicles, pedestrians, and other aspects of a driving scenario. Particularly, we used the data points of our identified agents on the near to crash cases and created the different scenarios. Then, we tested an Open-Loop ADAS algorithm using Driving Scenario in MATLAB/Simulink®. In an open-loop ADAS algorithm, the ego vehicle behavior is predefined and does not change as the scenario advances during the simulation. To test the algorithm, the driving scenarios previously created using the DSD were used. Accordingly, 5 driving scenarios with PET values less than 2 s generating using DSD app were tested in the Open-Loop model.

In the scenarios, an agent, which in those cases were cyclists, travels north and goes straight through an intersection. An ego vehicle, coming from the left side of the agent turns to the right. The ego vehicle was mounted with these sensors: (*i*) a front-facing radar for generating object detections; (*ii*) a front-facing camera and rear-facing camera for generating object and lane boundary detections and (*iii*) a lidar on the center of its roof for generating point cloud data of the scenario. After the scenarios were created, the

Open-Loop ADAS model `OpenLoopWithScenarios` was imported. In the model, a Scenario Reader block reads the actors and roads from the scenario file previously generated and output the non-ego actors and lane boundaries (see Figure 6).

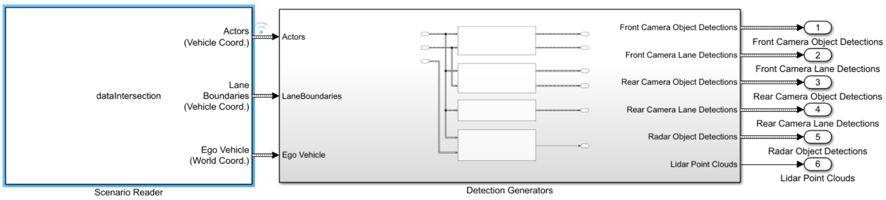

Figure 6 Example of an Open-Loop ADAS Algorithm using Driving Scenario.

The Scenario Reader block output the poses of the non-ego actors in the scenario and the left-lane and right-lane boundaries of the ego vehicle. The actor, lane boundaries, and ego vehicle poses were then passed to the `OpenLoopWithScenarios/Detection Generators` subsystem containing the sensor blocks (see Figure 7). The outputs of the sensor block in this model were in vehicle coordinates, where: the x-axis points forward from the ego vehicle, the y-axis points to the left of the ego vehicle and, the origin is located at the center of the rear axle of the ego vehicle. Because this model is open loop, the ego vehicle behavior does not change as the simulation advances. Therefore, the block reads the predefined ego vehicle pose and trajectory from the scenario file previously created.

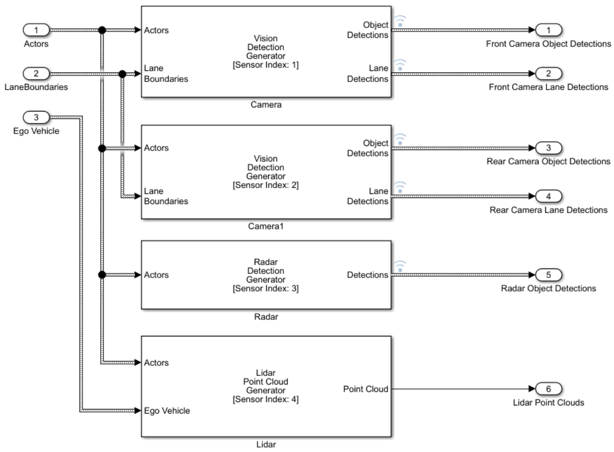

Figure 7 Detection Generators subsystem containing the sensors block.

Following, in the model, once the Scenario Reader block read the actor pose data from the saved file, the actor poses from the world coordinates of the scenario were converted into ego vehicle coordinates. The actor poses were then streamed on a bus generated by the block. Following, the actor poses were used by the `Sensor Simulation` subsystem, which generated synthetic radar and vision detections. The simulated detections were concatenated at the input to the Multi-Object Tracker block, whose output is a list of confirmed tracks. The concatenation block was done using an additional Detection Concatenation block.

The scenarios and sensor detections are visualized on the Bird's Eye Scope. The Bird's Eye Scope helps to visualize aspects of a driving scenario found in the Simulink® model. Using the Bird's Eye Scope, we can: (*i*) inspect the coverage areas of radar, vision, and lidar sensors; (*ii*) analyze the sensor detections of actors, road boundaries, and lane boundaries and (*iii*) analyze the tracking results of moving actors within the scenario.

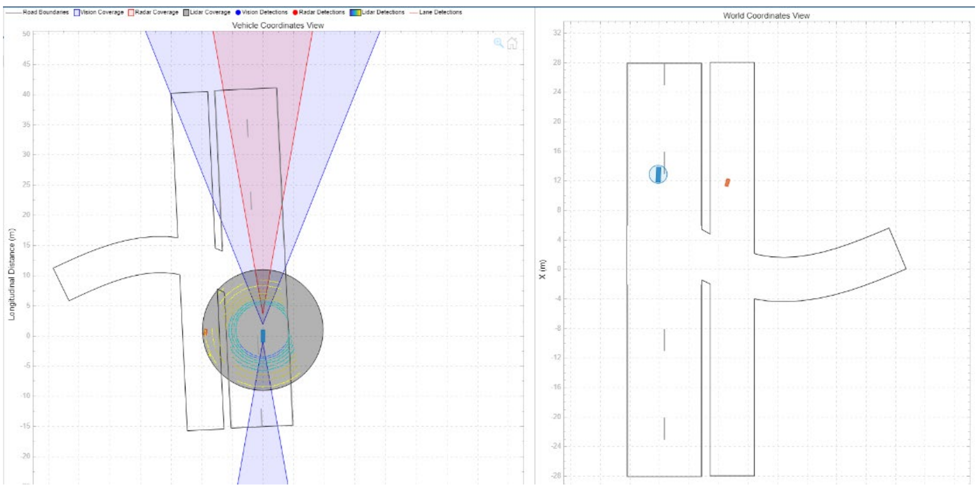

Figure 8 The Bird's Eye Scope of Scenario.

Figure 8 depicts a particular scenario where the car pass by right after the cyclist, in such scenario the PET was 1.701 s, which in turn can be considered as a serious traffic situation. The Bird's Eye Scope shows ground truth data of vehicle and cyclist. It also shows radar detection and vision detections.

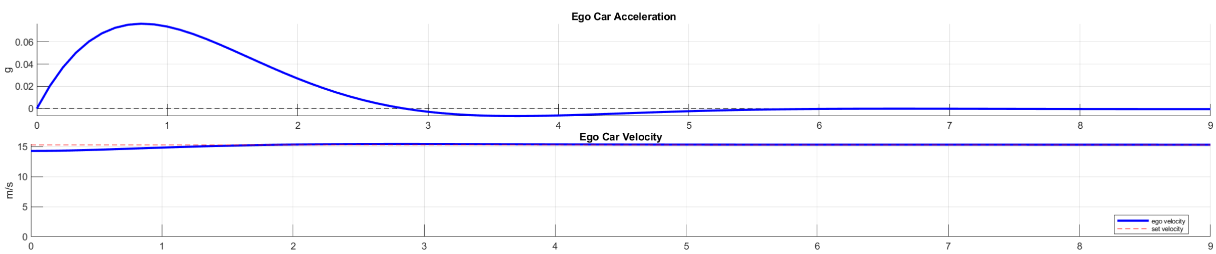

Figure 9 Simulation results

Figure 9 presents the simulation results obtained with MATLAB function `helperPlotAEBResults(logsout)`. The plot at the top shows the acceleration of the ego vehicle while the plot at the bottom shows the velocity of the ego vehicle. At the first second, the ego vehicle speeds up to reach the set velocity, which slightly speed down when turning to the right.
In particular, from the simulation results, it is evident that the driver was fully attentive and aware of the actor approaching to the intersection, however, in a hypothetic case where the driver is distracted, the use of cooperative perception and connected vehicle environment is of great importance to avoid a possible crash situation.

5. Conclusions, Lessons Learnt and Next Steps

With this pre-study we started with a review of relevant scientific literature regarding collective perception and the use of V2X communications. Concurrent with the literature review, we worked with the traffic measurement data in order to get a better understanding possible benefits of, and requirements for collective perception for improved ADAS and AD functions in real-world scenarios. From the literature review, one can conclude that there are issues such as the technology that should shape the future of V2X communication and the precise safety requirements that are still pending.

Furthermore, the reviewed works are based on deterministic traffic data input. When dealing with deterministic information strong assumptions are made, for example, it is assumed that precise information about the vehicles is known (i.e., positions, speeds, accelerations, etc.), it is expected that all actors are able to share information with each other and that no lane change maneuver is conducted. However, it is crucial to build the models using real driver data and assess them from statistical and behavioral standpoints.

As to the study of the collected data, we applied PET to measure how close an interaction between two actors was to a collision. PET was able to reveal the relationship between time and distance in the process of traffic conflict, however, the use of PET as an indicator of the closeness of a collision can be further investigated. The future work would pay attention to how different traffic scenarios compare to each other in order to be able to state more generalized results. Therefore, there is a need of more data. We could see that the number of PET values analyzed were not sufficiently large when divided into the traffic control levels.

Moreover, from the analyzed scenarios simulated in MATLAB, it was evident that the vehicles adjusted their speeds in advance since they could see an actor approaching to the intersection. However, the circumstances may change in case the vehicles do not have a line of sight with the actor approaching. In future work, more factors of the traffic simulation can be taken into consideration, for example, CAV penetration rate, since no existing transportation system can guarantee all vehicles are connected and automated.

The method of including infrastructure sensor in the sensor fusion when simulating the scenarios would also be investigated.

6. Dissemination and Publications

In addition to this report, a paper was submitted to the IEEE ICAV 2021 Workshop on Intelligent Connected and Autonomous Vehicles. The project results must also be presented in an online seminar to SAFER partners. Moreover, the project results will serve as a basis for an FFI project within FFI Efficient and Connected Transport Systems.

7. Acknowledgement

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