Cooperative Connected Smart Road Infrastructure and Autonomous Vehicles for Safe Driving

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***Abstract*—Connected vehicles (CV) and automated vehicles (AV) are promising technologies for reducing road accidents and improving road efficiency. Significant advances have been achieved for AV and CV technologies, but they both have inherent shortcomings such line of sight sensing for AV. Connected autonomous vehicles (CAV) has been proposed to address the problems through sharing sensing and cooperative driving. While the focus of the research on CAV has been on the vehicles so far, cooperative and connected smart road infrastructure can play a critical role to enhance CAV and safe driving. In this paper we present an investigation of connected smart road infrastructure and AVs (CRAV). We discuss the potentials and challenges of CRAV, then propose a scalable simulation framework for the CRAV to facilitate fast, economic and quantitative study of CRAV. A case study of CRAV on smart road side unit (RSU) assisted vulnerable road users (VRU) collision warning is conducted, where the identification of VRU such as pedestrians on the road by the AVs is compared with and without RSU assistance. The impact of the location of RSUs on avoiding potential collisions is evaluated for vehicles with different sensor configurations. Preliminary simulation results show that with the support of smart RSUs, the CAVs could be notified of the existence of the VRUs on the road by the RSUs much earlier than they can detect with their own onboard sensors, and collisions with VRUs can be reduced. This study demonstrates the effectiveness of the proposed CRAV simulation framework and the great potentials of CRAV.**

***Index Terms*—Connected vehicles, autonomous vehicles, connected intelligent vehicles, CAV, cooperative road safety**

I. INTRODUCTION

Road transport systems are facing increasing challenges due to the road accidents, congestion and pollution. It was reported by WHO that more than 1.3 million people died on the roads a year [1]. And more than 25,000 people lost their lives on EU roads in 2018 [2]. In the EU Road Safety Policy Framework 2021-2030 [2], a long-term goal of "Vision Zero" is set by EU to move close to zero deaths by 2050. In addition, traffic congestion costs approximately 90 billion lost hours per year and increases pollution. Connected vehicles (CV) and automated vehicles (AV) are promising technologies to reduce road accidents and improve road efficiency [3]–[6]. However, both AV and CV technologies have inherent shortcomings [3], [4], [7]. For example, AV sensors are limited to line of sight sensing and do not perform very well under in poor lighting, weather or road conditions. On the other hand, CV technology depends on message exchange to build mutual awareness, therefore a high penetration of CVs on the road is required to have a noticeable impact.

In view of the limitations of CV and AV, there are increasing research and development interests on connected and autonomous vehicles (CAV) technology. The sensor and computing resources of CAV vehicles are expected to be shared to build comprehensive perception of driving environments and cooperate on driving. 3GCPP is also developing enhanced cellular vehicle to everything (V2X) standards to support advanced driving uses, such as cooperative sensing, vehicle platooning, remote driving and cooperative driving. It is noted that the research reported on CAV so far is mainly focused on the vehicles so far, e.g., how to share and exploit the sensing among vehicles and how to cooperate on driving.

While cooperation on connected vehicles can help autonomous driving and reduce road accidents, there are still many cases where the safe and autonomous driving problems could not be solved by the vehicles alone. For example, detection of traffic lights and their states is widely known difficult for the AVs; detection of pedestrians behind vehicles parking on the road side at night is also very challenging. As pointed out in [2], there are four themes to tackle the road safety challenges and achieve the Vision zero goal, which are infrastructure, vehicles safety, safe road use (including speeding, alcohol and drugs), and emergency response, respectively. It is believed that cooperative and connected smart road

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infrastructure will be an important piece of the puzzle for the ultimate safe and green intelligent transport systems. We need not only intelligent and connected vehicles, but also smart and connected roads and infrastructure to support the CAVs. The smart roads can be configured adaptively to respond to traffic and weather conditions, such as changing the lanes to be used only by vehicle platoons and setting traffic lights. An example of the smart roads is the smart highway implemented in the UK, where a part of the highway hard shoulders are adaptively used for normal vehicles. For the smart infrastructure, the RSUs, transport control centers and telecommunication base stations all could play more important roles and make smarter decisions than disseminating traffic information. For example, the RSUs can use advanced sensors and computing resources to provide reliable sensing and edge intelligence to the fast moving CAVs, to avoid road accidents and support efficient driving.

Connected smart road infrastructure and AVs (CRAV) is receiving increasing attention and there are large pilots reported to have started. CRAV can bring in some important benefits to support CAVs, for example, enhanced sensing from sensors with better views, better detection and tracking of VRUs, coordination of CAV communication and driving, and gradual deployment of networks. Infrastructure assisted CAV has been investigated in a number of projects, such as [11] [12] [13]. While CRAV holds great potentials, research on CRAV is still at a very early stage. Research and investigation on CAV has been known very complex and challenging, due to cross disciplines of the technology, which includes automotive, driving planning and control, vehicle communications, computer vision and artificial intelligence. The introduction of smart road and infrastructure makes the research of CAV more challenging. While real test systems could produce reliable results, these real systems are extremely expensive and time consuming to build, and they are not scalable and flexible to do pressure testing and get deep insights for difficult and challenging scenarios.

In this paper we will present an early investigation of the CRAV. We first propose a scalable simulation framework for the CRAV to facilitate fast, economic and quantitative study of CRAV. It is noted that this framework is general and also applicable to CAV. A case study of CRAV on smart RSU assisted VRU collision warning is conducted, where the identification of vulnerable road users (VRU) such as pedestrians on the road by the AVs is compared under the contexts of with and without RSU assistance. The impact of the location of RSU on avoiding potential collisions is evaluated for vehicles with different sensor configurations. Preliminary simulation results show that with the support of smart RSUs, the CAVs could be notified of the existence of the VRUs on the road by the RSUs much earlier than they can detect with their own onboard sensors, and collisions with VRUs can be significantly reduced. This study demonstrates the effectiveness of the proposed CRAV simulation framework and the great potentials of CRAV.

The paper is organized as follows. Section 2 presents the related work. Section 3 presents a simulation framework for the investigation of CRAV. In Section 4 we investigate the case study of CRAV on RSU assisted collision warning. Simulation results and discussions are presented. Section 5 concludes the paper.

II. The State of the Arts

In the literature, the traditional approaches for improving RSE performances include adoption and enforcement of good driving laws and expansion of road network capacity. Recently there are modern approaches to reduce road accidents, mitigate accident impacts and improve road efficiency, which include ADAS and AV [3], CV [4] [5] [6], platooning [10], and accident detection and mitigation (ADM) [14]. In this section these relevant technologies are briefly introduced.

A. CV and V2X

CV uses vehicle to everything (V2X) communication technology to communicate with other road users and networks, including V2V, V2P and V2I. CV can transmit context aware messages (CAM) between vehicles to exchange host vehicle's speed, heading and brake status via dedicated short range communications (DSRC) [4], [7]. They can help warn drivers of impending crashes and hazards. Recently there are increasing research and standardization efforts in 3GPP to provide cellular V2X with low latency and high data rate communications [5], [6]. Direct vehicle communication based cellular V2X was specified in the latest 3GPP LTE releases. There is still a wide debate on deploying either DSRC or cellular V2X technologies. However, existing DSRC safety channel and cellular based V2V are prone to safety message congestion. Their communication reliability drops significantly with a high vehicle density. Unreliable and delayed message delivery can generate adverse safety consequence. In addition, the capacity of current V2V networks in terms of supported vehicles and the data rate of exchange messages is still limited, which is not sufficient for advanced RSE applications such as cooperative ADAS and platooning [10].

B. ADAS and AV

ADAS can support driving and reduce accidents. They are moving forward fast globally. Equipped with different sensors and advanced data processing algorithms, ADAS can warn drivers of impending danger so that the drivers can take corrective action, or even intervene on the drivers' behalf [3]. It can provide many enhanced safety features such as blind spot detection and forward collision warning (FCW). The ADAS is evolving towards self-driving vehicle, which has the highest automation level of AVs. Many global car makers and IT companies are racing to make self-driving vehicles. However, local sensing systems have line of sight sensing limitation and limited sensing range. According to the latest KITTI vision benchmark results, the accuracy of detecting pedestrians and cyclists is still low [8], [9]. Moreover, high definition maps are not robust to road changes and the driving systems are not intelligent enough to handle unexpected and challenging road situations. Therefore some car makers such as Tesla are developing self-driving cars with vision cameras sensor based solutions, which will more likely to encounter camera sensor related sensing problems.

C. Road safety and efficiency applications

ADM is critical for road safety and efficiency: once accidents happen, the control center and approaching drivers should be notified to control the accident scenes and prevent subsequent secondary accidents [14]. However, existing ADM systems are still mainly relying on local sensing and computing resources [14], which may not be able to provide fast response. Platooning has large potentials of increasing traffic capacity and fuel efficiency by employing a short headway [10]. The main control of a platoon aims to ensure the vehicles in a platoon move at a consistent speed and maintain a desired spacing. A key task in platooning is determining vehicle space. In the earlier studies radar based sensing systems are used to determine the spacing to the front vehicle. Recent V2V communication was applied to determine and control vehicle spacing, for example, V2V based space control was successfully test on the Helm project with DAF trucks [1] But the existing V2V communications could not satisfy the very high communication requirements from platooning applications. More advanced driving applications such as remote driving and cooperative driving are expected to be supported by 3GPP 5G V2X standards.

D. Simulation and Real Pilot Test of CRAV Systems

As we discussed beforehand, implementation and evaluation of the CAV and CRAV systems are very challenging. While there are simulation based study of the subsystems for CAV system, to the best of knowledge, there is no reported complete simulation of the CAV system (including V2X communication, sensing with computer vision and autonomous driving applications). For the simulation of V2X communications, there are widely used environments, such as NS-2, NS-3, OMnet, OPNet. For the sensing with sensors in both CAVs and RSUs, the widely used deep learning engines include Pytorch from Facebook, Tensorflow from Google and deep learning toolbox from Matlab. Many deep learning models have been proposed for object detection and segmentation. For the autonomous driving, widely used software tools include CARLA and CarSim. There are some pilot systems reported over the world to verify the concept of CRAV and its performance. But the real system testing approach is not scalable, slow and difficult to test rare and dangerous cases. Therefore alternative approaches should be proposed for the implementation and systematic evaluation of CRAV system.

III. Cooperative CRAV Research and Simulation Framework

According to the aforementioned discussion, it is clear that there are still many research challenges faced by CAV and CRAV, for example, poor object detection at poor lighting and object occlusion conditions. Cooperation among the CAVs and among CAVs and smart RSUs is critical to improving the perception of driving environments and reduce road accidents. However, there are also new barriers introduced by the cooperation of CAVs and RSUs. For example, to enable cooperative sensing among the CAVs and RSUs, several research issues need to be tackled, which are discussed below.

- The deep learning models developed for object detection (such as Faster-RCNN and YOLO3) and tracking are well known data driven and operate in a black-box manner. The object detection results are not fully reliable. It will be very difficult for the CAVs to trust and accept the sensing results from neighboring CAVs with local ones.
- In the mobile CAV networks, the network topology is dynamic and the CAVs usually have short connection period with each other. It can be difficult to trust other CAVs and cooperate with each other.
- Accurate localization of the detected objects locally is also important and challenging for cooperation of CAVs and CRAVs.
- For fusion of sensing data from other CAVs or RSUs, the coordination systems at the other CAVs or RSUs needs to be converted to the local coordinate system.

Apart from the above research issues for cooperative sensing, there are also further research issues on the design of reliable and effective cooperative driving and road safety applications, evaluation and validation of the cooperative driving and safety applications for the CAV and CRAV systems. In this paper, we will focus on the simulation of CRAV systems for fast and scalable evaluation of CRAV road safety applications, which is important to understand the benefits and limits of the cooperative CRAV systems, support decision making, and facilitate design and planning of CRAV systems.

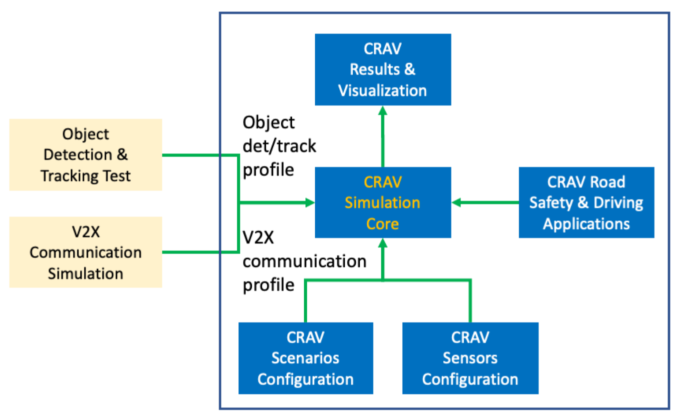

Fig. 1. Illustration of the offline communication framework for CRAV simulation.

A. Integrated CRAV Simulation Framework

Compared to the real CRAV test systems, CRAV simulation is a much cheaper and more flexible for performance evaluation and system validation. With the support of the

[1]https://www.helmuk.co.uk/

available tools and libraries for simulation, design of and setting up the CRAV systems for simulation could take much less time compared to these for real test systems. An easy and intuitive framework for simulation of CRAV systems is to integrate simulation of all the subsystems. For one simulation of CRAV safety application under the integrated simulation framework, the V2X communication system is simulated at the packet levels following the communication protocols, the local sensing will be simulated at frame levels with application of pre-trained deep learning models, and the movement of the CAVs will be simulated with predefined trajectory. The fusion of local and shared detected objects and/or tracks is then performed according to the simulation outcomes from the communication and local sensing, which is further used for the simulation of the cooperative driving and safety applications.

B. Decoupled CRAV Simulation Framework

Running simulations under the integrated framework could be very slow to obtain credible performance results. It is therefore important to design alternative scalable and fast solutions. In this paper we propose a fast and scalable simulation framework, which is called decoupled simulation framework. Under this framework, the V2X communications is simulated separately from the CAV driving simulations, therefore it can enable fast simulation of the CRAV systems. Optionally the object detection and tracking subsystem can also be evaluated separately offline.

The overall decoupled CRAV system simulation framework is presented in Fig. 1. Next we will briefly introduce the functionality of the subsystems presented in this simulation framework.

1) Simulation of V2X Communication: Before the simulations for the CRAV systems are conducted, the V2X systems are simulated first. Either DSRC or cellular V2X communication technologies can be simulated with various road layouts, CAV densities, message side, allocated bandwidth and vehicle speeds, etc. Different channel models should be used according to the driving scenarios (such as highway and urban driving). The simulations will be run at packet level and follow the V2X communication algorithms. The simulations of the V2X communication technologies is expected to produce the statistic performance of packet successful ratio and delay against communication distance. The statistic performance of the V2X communication will be used to create communication profiles (e.g., performance curves against distance) and stored for further use.

2) Object Detection and Tracking Test: Sensing plays a critical role for intelligent vehicles. There are several widely accepted sensors for CAVs, including cameras, radars and Lidars. They can be installed at both CAVs and RSUs. The simulations of the object detection and tracking can be done separately. The object detection is simulated at frame levels with the application of deep learning models for inference. The accuracy and confidential score of object detection will be evaluated against object distance, lighting and weather conditions, object categories, object occlusion and sizes. The statistic object detection performance is also used to create object detection profiles (e.g. performance curves against distance and occlusion) and stored for further use in CRAV simulations.

3) Core CRAV Simulations: The main CRAV simulations will be run by the CRAV simulation core. In the separate simulation framework, the simulation core will accept V2X communication profiles and object detection profiles as input. The CRAV simulation scenarios and sensors will be configured in advance, including the road layout, vehicles on the road and RSUs, road users and VRUs, trajectories of the CRAVs, sensors installed at the CAVs and RSUs. In addition, different road safety and driving applications can be specified.

After the configuration of the CRAV simulations, the core CRAV simulations can start with regular updating of the actors (CAVs, RSUs and VRUs) positions and status. At each simulation step, the object detection and tracking will be performed for the actors with local sensors by referring to the object detection profiles (instead of applying deep learning models for each frame). Then depending on the configuration of cooperation modes for the cooperative driving and road safety applications, the local sensing results could be made available for sharing through V2X with neighbor actors. The successful reception of the shared sensing results will depend on the outcome of communication among the interested actors, which will be simulated in a simplified approach by looking up the V2X communication profiles. Whether a transmitted message is successful or not is determined by the packet successful ratio derived from the offline V2X communication simulations. If a message with shared sensing data is received from neighbor actors, the shared object detection and/or tracks can be accepted and fused with the local detection or tracking. Depending on the cooperative sensing, actions for cooperative driving and/or road safety applications will be taken.

The above processing for the core simulations will repeat until a preconfigured number of simulation steps. Then the results for the cooperative driving and road safety applications will be collected and visualized.

IV. A CASE STUDY OF CONNECTED SMART ROAD AND AVS

The proposed separate simulation framework is general and can be applied to study a wide range of driving and safety applications. In this paper we investigate a case study of CRAV on smart RSU assisted VRU collision warning. In this case study when the vulnerable road users (VRU) such as pedestrians on the road can be identified by the CAVs is investigated under the contexts of with and without RSU assistance. The impact of the location of RSU on avoiding potential collisions is evaluated for vehicles with different sensor configurations.

A. Simulation Settings

For this case study we create a scenario as shown in Fig. 2. In this scenario, we consider a RSU, two CAVs with LTE V2X radios and camera sensors, a parked bus which may block the views of the CAVs approaching from the front. A passenger attempts to cross the road. There are also a number of vehicles without V2X radios and sensors for road perception. The road is 8 meters wide with two lanes. The RSU is located at (95, -10). It has two cameras pointing towards to the road with different directions. The two CAVs moving with a speed of v meters/second. The initial location of CAV1 and CAV2 is (-20, 3) and (-10, 3), respectively. The parked bus is located at (d, 3) where d is configurable variable with range of [5, 80]. It has a length of 8.5 meters, width of 2.5 meters and height of 3.5 meters. The pedestrian is located at [d+10, 3.8].

The RSU monitors the VRUs (the pedestrian in this use case) on the road, and share the tracks of the CAVs and VRUs to the other CAVs. The CAVs will monitor the VRUs as well with only the local onboard cameras if non-cooperation mode is configured. If cooperation model is configured, the tracks from the RSUs are fused with the local tracks. Depending on the tracking outcomes, a warning of VRUs on the road and potential hazards will be generated for the driving and necessary actions can be taken if needed.

The communication settings follow the configuration used in [6], with a 10 MHz bandwidth for LTE V2X. The communication curve is approximated by function: y = p(x) = 1 - 0.3*(d/x).

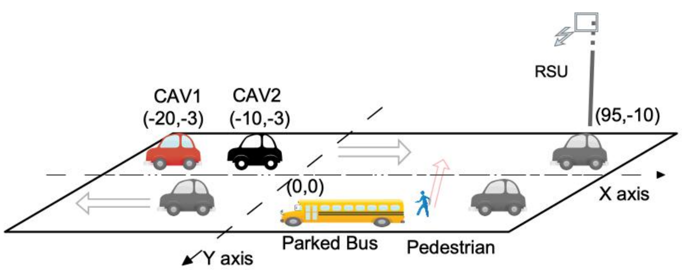

Fig. 2. Illustration of cooperative CRAV scenario.

B. Simulation Results

With the above system configurations, simulations were run in Matlab with autonomous driving toolbox to collect results [23]. The CAV speed v is configurable, which is set to 12 m/s in this study. Two set of results are presented in Fig. 3. The first set of results shown in dashed lines refer to the allowed response distance of CAV1 and CAV2 with detections by only local cameras. The second set of results refer to the allowed response with fused tracks from the RSU. The allowed response distance (ARD) is defined as the distance of the CAVs to the pedestrian in the X axis direction at the first time the CAVs are aware of the pedestrian on the road, before the CAVs pass the pedestrian.

It can be observed that without the assistance of the RSU, the CAVs can't see the pedestrian behind the parked bus until they are very close to the pedestrian. The ARD of the two CAVs is very close (around 13 meters) and does not change with the location of the parked bus, which is not sufficiently large for the driving to stop before a potential collision with

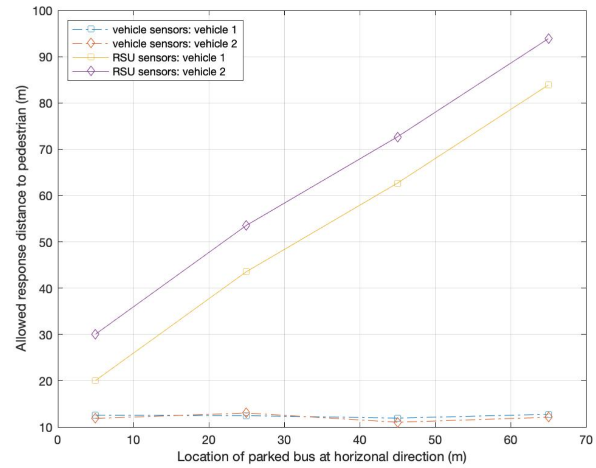

Fig. 3. Simulation results on the response distance with and without RSU assistance on cooperative sensing.

the pedestrian. On the other hand, with the cooperation of the RSU and CAVs, the CAVs can receive the shared tracks from the RSU and be aware of the crossing pedestrian much earlier. And the ARD with the RSU assistance increases linearly with the d.

V. Conclusions

In this paper we presented a separate framework for scalable and fast simulation framework for cooperative connected road and autonomous vehicles (CRAV). We analyzed the technical and non-technical challenges faced by cooperative CRAV. Preliminary simulation results show that with the support of smart RSUs, the CAVs could be notified of the existence of the VRUs on the road by the RSUs much earlier than they can detect with their own onboard sensors, and collisions with VRUs can be significantly reduced. This study demonstrates the effectiveness of the proposed CRAV simulation framework and the great potentials of CRAV. In the future we will investigate more cooperative CRAV related research problems, implement cooperative RSE applications and demonstrate their potentials.

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