Towards a Real-Time Emergency Response Model for Connected and Autonomous Vehicles

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Abstract
Recently technological advancements in the automobile and transportation sector have gained significant interest from governments, industry leaders, and citizens. Together with Autonomous Vehicles (AV) and Connected Vehicles (CV), Connected-Autonomous Vehicles (CAV) have made a revolution in these sectors. Emergency Vehicles (EVs), such as ambulances, fire trucks, and patrol cars, are essential to our daily traffic life. Each of EVs has a different purpose, but all have their urgency and importance, and any time passing may cause the death of life. Thus, whenever other vehicle drivers encounter an EV on the road, they must yield to the EVs. Therefore, a CAV system that can detect EVs will significantly improve these issues. According to the Society of Automotive Engineers International (SAE), in today's autonomous vehicles, most of them are less than Level 5, and car manufacturers assume the driver will take back control. Still, most autonomous vehicles mainly rely on their vision sensor instead of their sound sensor. Thus, when the system notifies the driver that the EVs are already close to them, it may be dangerous for the driver, pedestrians, and passengers in the vehicle. This paper proposes a conceptual framework and discusses a related methodology to support such a real-time emergency response model for CAV.

Keywords
connected-autonomous vehicle, emergency vehicle, emergency response, real-time response, driving assistance technology, the Doppler Effect, exceptional handling, control strategy, machine learning

1. Introduction

Recently technological advancements in the automobile and transportation sector have gained significant interest from governments, industry leaders, and citizens. Autonomous Vehicles (AV) technology enables vehicles to be controlled by precise, fast responding computers instead of error-prone and slowly responding human beings; Connected Vehicles (CV) allow infrastructure units and vehicles to share high-resolution information through wireless connectivity that can communicate to support interaction with their internal and external environments in real-time, e.g., for traffic systems and between individual vehicles. Connected-autonomous Vehicles (CAV), which integrates the best of both AVs and CVs, have revolutionized these sectors [1, 2].

According to the report of the Society of Automotive Engineers International (SAE) [3], the level of autonomy of vehicles ranges from Level 0 to 5. Level 0 concerns entirely human-operated vehicles, while Level 5 vehicles are fully automated. For example, in Level 1 of automation, the vehicle may assist the driver with tasks like steering or acceleration. Shared Autonomous Vehicle (SAV) should be considered at least Level 2 of vehicle automation. It enables the driver to remain fully engaged with the driving task but gradually transfer control from human to machine. Level 2 automation features include adaptive cruise control and automatic emergency braking. In the industry, most CAV classifies as Level 4 of automation, while automotive companies have carefully explored Level 3. Under some circumstances, the machine and the human might be sharing of controlling the driving task. Such cases can be dangerous for the driver and passengers due to the spare time between controlling exchange and human-decision making. Level 4 of autonomous capability means cars can self-drive in most conditions without human intervention. However, there are many open design challenges, including technical, ethical, and regulatory matters. A completely automated vehicle (Level 5) can perform all driving functions under all conditions. In this situation, humans are just passengers.

CAV can excel in numerous advantages for smart city citizens by offering them better and more effective transportation services, such as dramatically reducing car crashes and driver fatigue [4, 5]. CAV offers benefits for private and public transportation. It includes vehicles

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as private and service (e.g., Uber) cars, buses for public transport (which includes school buses), and trucks (e.g. garbage collectors and agricultural trucks). CAV benefits are achieved by collecting relevant information from the CAV's context, such as geolocation, date and time, and other individual attributes like age, address, gender, and income. Therefore, CAV can infer an individual's interests, traits, beliefs, and intentions.

Many of today's automated vehicles lose track of the lane position when the lane markings are absent. For example, erroneous lane marking recognition contributed to a fatal crash of Tesla cars in California in 2018 [6]. CAV can address such issues since it can be connected through external interfaces, like Wi-Fi, Bluetooth, Global Positioning System (GPS), and Tire Pressure Monitoring System (TPMS). Moreover, internally, CAV works with a Controller Area Network (CAN), connecting different Electronic Control Units (ECU) as the engine itself. On the one hand, these connections are necessary to provide basic (e.g., driving) and advanced features (e.g., autonomous driving and entertainment) to involved persons, such as drivers, passengers, and pedestrians.

The application of CAV in real-time response for Emergency Vehicles (EVs) has resulted in great improvements in the efficiency of the process. EVs, such as ambulances, fire trucks, and police cars, are essential to our daily traffic life. Each EV has a different purpose, but all have their urgency and importance for emergency response and saving a life. Thus, whenever a vehicle driver encounters an EV on the road, the driver must yield to the EV in a safe condition.

Usually, the EV has vision and audio devices to remind drivers and pedestrians of their existence, but these devices may sometimes be less effective in a noisy surrounding environment [7]. In 2019, 170 people were killed in crashes involving emergency vehicles, most of which were non-emergency vehicle occupants in the United States [8]. To address this issue, Advanced Driver Assistance Systems (ADAS) such as adaptive cruise control, blind-spot object detection, and lane departure warning have been designed to improve driving safety and support CAV. However, to our best knowledge, there is still not much research work in ADAS for the real-time emergency response for EVs, especially in CAV.

This paper aims to study a real-time emergency response model for CAV (SAE Level of autonomy 3), specifically for EVs, using a hybrid approach embedding either vision and sounds sensors, aiming to detect and localize the EVs by the vision and siren detection system, which will be discussed and analyzed the increase of accuracy of distance and identification measures to ensure sustainable and safe operation during normal and emergency conditions and consideration of current related codes and standards environment.

The paper will survey and evaluate CAV based on a detailed analysis and enhancement of technical aspects and operation, safety, and reliable performance for the emergency environment under pressure. The proposed model of CAV will have a routine for Key Performance Indicators (KPIs) based on functional operational and safety requirements, resiliency measures, risk analysis, and Safety Integrity Level (SIL) allocation. Verification and validation will be evaluated in the related Electronic Control Units (ECUs) with relevant standards or codes such as the National Electrical Code/National Fire Protection Association (NFPA) 70, Canadian Electrical Code and the International Electrotechnical Commission (IEC) standard and Underwriters Laboratories (UL) standard and other codes/standards/regulations such as the working document provided by International Organization for Standardization (ISO): ISO 26262 "Road vehicles - Functional safety" [9], and ISO 21434 "Road Vehicles – Cyber Security Engineering" [10].

The remainder of the paper is organized as follows: Section 2 reviews the related scientific works present in the literature in this work's area. Section 3 presents a proposed conceptual cooperative framework and methodology for real-time emergency response for Connected-Autonomous Vehicles. Section 4 concludes the paper, presenting a brief discussion and the found limitations.

2. Literature Review

Safety risks may bring implications for CAV passengers, other vehicles, pedestrians, and road infrastructure to understand human aspects and perceptions towards CAV, such as trust [11, 12], driving style [13], and physical safety of pedestrians and city infrastructure [14]. These numerous safety issues related to security risks may influence the consumer's trust in purchasing CAV solutions [11].

There are many causes of EVs accidents. In personal factors, the EVs drivers usually drive under high pressure because of the time pressure, long shift hours and code 3 running thinking. In code 3 running, the driver can exceed the speed limit and does not have to follow the traffic signs in order to save the most time [15]. In environmental factors, drivers usually drive in unfamiliar environments or even disaster areas, and intersections are the most frequent places for EVs to be involved in car accidents [15]. In the physical feature, fire trucks and ambulances have a larger volume and are more likely to cause danger when they are driven together with other vehicles. Summing up the above factors, we can understand the threat of encountering EVs on the road. Their task nature is more dangerous than general road driving, especially since most vehicle conflicts occur at intersections. Therefore, if the traffic signal light can respond to the situation on the road and save time on the ambulance, it can also reduce the risk in the intersections. According to the task of EVs, there is usually time urgency, so for the surrounding vehicles, the best way to respond is to slow down and stop as soon as possible so that emergency vehicles do not have to be distracted by other vehicles. However, even the Intelligent Transport Systems (ITS), which include the protocols of communications between CAVs and the intelligent traffic, could be compromised by cyber-attacks becoming susceptible to safety risks [16].

Advancements in the CAV industry also open opportunities for creating a new profile of drivers. Among the most promising approaches, CAV is the first alternative for independent visually impaired drivers [17]. According to the World Health Organization (WHO), more than 1 billion people live with some visual impairment in the world [18]. WHO shows that 36 million of them are blind, and the majority of those people are over 50 years old. Indeed, population aging is a worldwide phenomenon that is expected to bring economic consequences [19]. Building CAV that the elderly population can use can help the industry to overcome the economic challenge. However, to this end, accessibility of CAV becomes imperative for the sector [17]. Besides the elderly and people with visual impairments, advances in CAV also open opportunities to enhance children's transportation. For example, autonomous school buses may benefit their independent transportation, or, even, parents may use private CAV to drive their kids to school.

Driving essentials scenarios include, but are not limited to, studies on Computer Vision (CV) to enhance CAV capabilities of (partial or complete) self-driving, Artificial Intelligence (AI), Cloud computing, and machine learning, among other computational domains concerned to enhance essential driving functionalities [20, 21, 22, 23]. Essential functionalities cover GPS services (to allow autonomous driving) and a range of sensing technologies suitable for driver's and passenger identification, including vehicle and road infrastructure detection and parking assistance. This scenario involves Computer Vision techniques and route generation, which come from Computer Science and Automation Engineering backgrounds. Another technology, such as the blockchain, has already been embedded in CAV, considering its efficient performance mechanisms for decentralized distributed storage and security management of big data [24, 25].

The main stakeholders in this real-time emergency response scenario are the automobile sector, the mobile application market, and average drivers and passengers. An interface for this scenario can assist drivers in selecting and monitoring their driving routes, including contextual stops for either safety or personal matters. The emergency response model component may collect CAV's contextual information, like the vehicle's fuel or another engine status. Then, it uses such information to determine if the GPS route must add a stop at the gas station, for example. In the context of smart technology, the interface may have access to the fridge or food storage information to add a stop at the supermarket or grocery store so that the human can purchase supplies. These contextual GPS scenarios can offer more effective itineraries for the drivers. They can include everything from picking up colleagues to sharing a ride for work to syncing the driver's agenda or adapting routes to traffic information, among other individual behaviors.

In previous research, the methods for detecting sirens from EVs can be divided into two different approaches. The first approach is to identify whether the data contains siren sound based on the siren's characteristics, such as high-frequency and low-frequency, or cyclical nature [26, 27]. However, this method does not perform well in noisy environments, especially in urban areas. The second approach is to extract the siren signal from background noise [28]. For example, Fazenda et al. employed the least mean squared algorithm to create a noise canceller to extract the target signals [29]. Nishimura et al. proposed a data embedding method for the vehicle location into the siren sound [30]. This research tends to extract the siren signals from background noise, including lots of parts in real traffic life, by considering the Doppler Effect. The Doppler Effect is that the sound frequency will vary according to different speeds, so the siren frequency in real life may differ from the spectrum we observe. Referring to the siren datasets we collected from the Web, Schröder et al. showed that some audio software could help to mimic the Doppler Effect in the datasets, such as Adobe Audition 1.0 [31].

Our hybrid approach aims to localize the siren by a time delay estimation method and a sound intensity probe method in the Path Planning function. For example, Fazenda et al. showed that the accuracy of the time delay estimation method is better in the distance between the emergency vehicle and the driver in a long distance. But if it is in a short distance, the sound intensity probe method can also get a higher accuracy [29].

Different projects have made great efforts to advance in the CAV areas. Big technology and automotive companies and universities have been working together to advance the projects, designing vehicles and developing different algorithms and drive systems split into different levels of autonomy.

Uber, in partnership with Carnegie Mellon University; Lift together with General Motors; and Didi, with Japanese automotive companies, have been building self-driving cars and ride-sharing services with level 4 and planning to build level 5 of autonomy. Uber, Lift and Didi are companies that provide mobility services and have a great power of traffic data collection, which is the key to developing and improving their automation system and models [32]. AutoX, in 2018, built an advanced full-stack self-driving AI platform in partnership with Alibaba Group, Chery automotive, NVIDIA, and other companies to build SAE Level 2 and 3 assistive-driving vehicles, including RoboTaxis and RoboTrucks. The companies' idea for the next decade is to develop a full (Level 5) autonomous car, beginning in 2021 with the first Fully Driverless RoboTaxi Service to The Public in China [32, 33].

Google Waymo, in partners with automotive companies such as Fiat-Chrysler, Audi, Toyota, and Jaguar, has been working on self-driving vehicles of autonomy level 4, operating the Waymo Driver, a commercial autonomous ride-hailing service, in San Francisco, California. Recently in 2020, Waymo started the operation of Waymo Via, transporting commercial goods that use autonomous vans and trucks [34]. The Apollo project, Baidu's open-source self-driving platform, was created to test and improve the CAVs' motion planning and vehicle control algorithms to aim the driving safety and riding experiences. AVs such as the Lincoln MKZ Sedan and the Ford Transit Van were used to train their dynamic models by real-world road data collected from Apollo autonomous vehicles driving on urban roads [35]. The Apollo platform was its 6.0 version at the end of 2020. The union of efforts of the big technology companies and automakers to conceive powerful Autonomous Driving Systems (ADS), and consequently build fully Self-driving cars have provided great technological advancements aimed at reaching common goals such as enhancing safety, decongesting roadways, saving time for users, reducing greenhouse gas emissions, and ensuring mobility for all people, including the disabled and the elderly [36].

To enhance situational awareness in CAV, our proposed model will also incorporate the research work in computer vision tools such as geolocalized photos and videos of the situations into the proposed model [37]. Furthermore, the model is expected to be implemented by a machine learning approach based on Support Vector Machine and Neural Network with the datasets we collected for this research and responded to the real-time input data [38].

This research will consider the operation of CAVs that face some technical challenges, such as the instability in some operating conditions due to the dynamic response of emergency traffic scenarios on a real-time basis. Most of the CAV mainly rely on their vision sensor instead of their sound sensor. One of the related research areas is the hearing impaired [39, 40]. In recent years this research area has gradually begun to move into CAV [36, 41]. Therefore, we believe that detecting the approaching EVs using both a vision sensor and a siren detection system is essential in the future.

3. A Conceptual Framework and Methodology

CAVs are under various scenarios and operating conditions of residential, industrial facilities, transportation electrification, and grid-connected integration. Therefore, it should provide a comprehensive evaluation of the safety risks during the operation of CAV by identifying hazards and estimating risks in different operating conditions and modes. Codes and standards roadmap should be performed based on fault propagation modeling and analysis, simulation and evaluation will be presented and analyzed by independent protection layers for all possible normal and abnormal operating conditions. Besides, evaluation and validation of technical, economic, safety, reliability, and availability with risk factors, life cycle costing, and environmental assessment will be discussed.

The research will consider the technical requirement of CAV for safety and performance evaluation. It will consolidate the currently available codes and standards of CAV and propose new evaluation criteria for real-time emergency responses, to support CAV standards. CAV has two aspects: hardware and software. Hardware governs sensors such as Vehicle-to-Vehicle (V2V), Vehicle-to-Grid (V2G), Vehicle-to-Infrastructure (V2I) and Vehicle-to-Everything (V2X) technology, and actuators. Software deals with processes of perception, planning, and control. V2X technology components V2V and V2I allow the vehicle to communicate by receiving information and talking to other systems in the environment. These environmental communication systems can be other vehicles or smart city light-changing signals. CAV should be tested according to their ability to transition with city speed restrictions during an emergency.

During autonomous driving, one of the most dangerous maneuvers is lane changing. Even with ADAS, lane change is still very complex and potentially dangerous. ADAS systems should be tested on features like Adaptive Cruise Control (ACC), Autonomous Emergency Braking (AEB), and Lane Keep Assistant (LKA). Planning operations should be tested under different scenarios to test the vehicle's ability to adapt to road circumstances. According to recent literature, the Path Planning component of CAV comprises three functions: Mission Planning, Behavioral Planning and Motion Planning. A typical task of each function is outlined as follows: (1) The Mission Planner: High-level decisions such as determining pickup destination locations and road selections achieve the target mission. (2) The Behavioral Planner: Dynamic ad-hoc decisions such as lane change, intersection crossing, and overtaking. (3) The Motion Planner: Collision avoidance, obstacle avoidance, alarm generation, etc. The proposed model will be incorporated into Path Planning.

3.1. Evs Identification Process

In Figure 1, Our proposed EVs identification process will start by detecting the approaching vehicle based on visual and sound sensors. There are usually two ways to detect EVs. One is to see their unique appearance, and the other is to hear their siren sound. In the siren sound detection, we first identify which type of emergency vehicle it belongs to and extract the specific siren sound from the background noise. After we extracted the siren sound, we used the time delay estimation method and sound intensity probe method to localize the direction of the sound. From the previous research [29], the time delay estimation method has better performance in long distances than the sound intensity probe method. Thus, we can decide the direction of the siren sound detection.

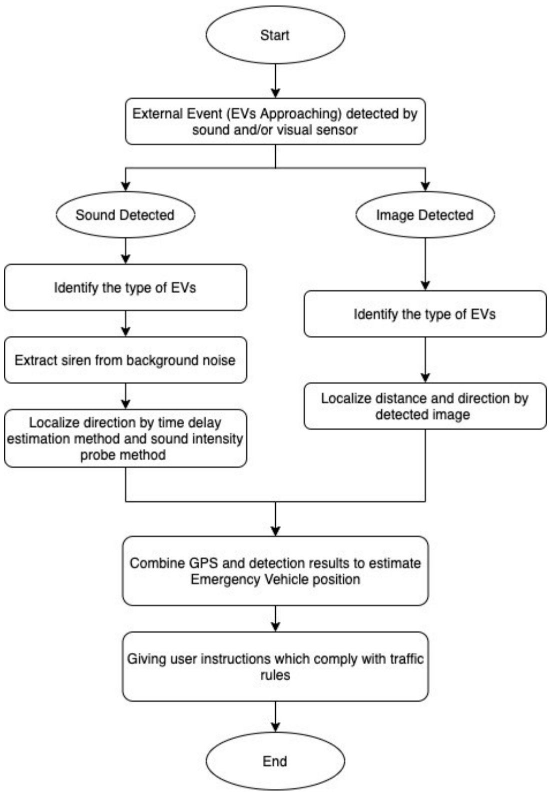

Figure 1: EVs Identification Process.

In visual detection, we first detect the type of emergency vehicle and use the image we captured and the distance we detect from Light Detection and Ranging (LIDAR) to localize the direction and the position of the EVs. Combine the above information and use the GPS to help predict the possible path of EVs and provide driver information so that appropriate responses can be made as soon as possible. If our route is interleaved with the route of EVs, we will respond. If there is no conflict, we will continue to observe but do not require a response. Basically, we hope we can detect both sound and visual detection to give complete information to the driver. If we can not detect the precise position, our system can probably predict the possible position to give the most appropriate response.

3.2. Algorithm

Then we introduce our Emergency Vehicles response algorithm. Table 1 is a brief conceptual introduction. When we detect approaching EVs, we first evaluate our speed. If our speed is higher than a certain speed, we gradually decrease the speed to maintain safety. Then when the position of EVs has been confirmed, the system starts to perform the lane change to yield to EVs. The method of changing lanes will first detect vehicles in the vicinity, according to LIDAR, which can detect vehicles within a radius of 100 meters.

```
Result:
def yieldToEVs():
  Matrix = detectSurroundVehicle();
  # By Using LIDAR to detect vehicles
  changeLane(Matrix);
  # change lane according to the vehicle matrix
  while Emergency Vechicles is detected do
    if speed is above certain speed then
      slowDown();
      # slow down to certain speed
      if EVs' location is confirmed then
        yieldToEVs();
        vehicleStop();
      end
    end
end
```

Algorithm 1: Algorithm of Emergency Vehicles Response

Based on the results scanned by LIDAR, we can form a vehicle matrix according to our lane and then plan how to yield EVs based on the vehicle matrix. In Canada, the Ministry of Transportation [42], in its traditional rules, stipulate that when EVs are encountered, they pull as close as possible to the right edge of the road. However, according to the real situation, it is not always the best option to pull to the right. We should make the most space according to the traffic conditions. When we yield the position to EVs, the best way is to stop and let the EVs drive safely. After all, any vehicle movement can cause distractions in our EVs driver.

3.3. Conceptual Cooperative CAV system

By using the sharing property of the CAV, we aim to create a comprehensive safety standard and system. Figure 2 is our conceptual cooperative CAV system; all the CAVs can do collaborative sense and computation. In addition to the communication between vehicle and vehicle (V2V), the communication between the vehicle and the traffic lights (V2I) can also significantly save time for the EVs to reach the destination. Usually, the biggest problem encountered by EVs is the traffic jam on the road or the danger encountered when executing 'code 3 running', on the way to an emergency. Our EVs response ADAS can collaborate with other ADAS, such as Adaptive Cruise Control, Autonomous Emergency Braking, and Lane Change Assistant, to give corresponding responses automatically. As for the interaction between humans and vehicles, in the process of automated response, humans need to supervise and be able to intervene. For example, in Tesla's autopilot system, people need to put their hands on the steering wheel to ensure safety when performing lane changes. Accidents caused by automated failures in the response of EVs can seriously affect lives. At present, a few fatal vehicle accidents occur on autonomous vehicles. Therefore, before we can fully guarantee the driving safety of autonomous vehicles, appropriate human supervision and intervention are necessary.

ADAS can outperform humans in some automated operations, thus promoting traffic safety and resulting in the development of autonomous vehicles. To achieve the driving safety of autonomous cars, some standardized methodologies were created. Projects such as the Waymo Driver and AutoX developed the ADAS of their Self-driving cars using the ISO 26262 "Road Vehicles - Functional Safety," which presents guidelines applied to safety-related systems that include one or more electrical and/or electronic systems in automobiles. Due to the necessity of dynamically and automatically driving awareness, with lanes and vehicle detection, as well as collision avoidance, the CAV systems have continuously improved their automobile intelligence and connectivity capabilities, increasing the focus on cybersecurity. Standardized methods of cybersecurity, such as the ISO 21434 "Road Vehicles - Cyber Security Engineering," have been adopted, which specifies requirements for the whole life cycle of automotive products of engineering-related cybersecurity risk management for road vehicle electrical and electronic systems and their components and interfaces [43].

Our system development will comply with ISO 26262 and ISO 21434. The software development life cycle in ISO 26262, from design to implantation and validation, will be followed. In addition to software development, appropriate information management, including process records, will be used to maintain complete traceability in dynamic and static data and properly manage risks, and our ADAS will be reviewed according to standard security requirements. From the cybersecurity perspective, the work will follow ISO 21434 while security will be considered in the development and deployment process, embracing the Security by Design approach, considering requirements since the adoption of secure wireless connection protocols to the usage of encryption in information transmission. For every information transmission, an appropriate incident response mechanism will be initiated, which will include methods for determining actions of progress or remediation and vulnerabilities analysis, that will consider the potential damage.

4. Conclusion

The operation of CAVs faces some technical challenges, such as the instability in some operating conditions due to the dynamic response of traffic scenarios, such as emergency vehicle response. Therefore, the SAE classifies the vehicle from Level 0 to 5 based on the automation capabilities. In today's CAV, most of them are in Level 3, and car manufacturers assume the driver will take back control during the emergency in real time. However, drivers should stay aware of automation limitations, and the manufacturers should make a warning system that can give warnings far ahead of time. Nowadays, most CAV mainly rely on their vision sensor instead of their sound sensor. Our hybrid approach aims to detect and localize the EVs by the vision and siren detection system. We believe that detecting the approaching EVs using both vision and sound sensors are essential in CAV, increasing the accuracy of distance and identification measures. The research direction covers codes and standards for all control and communication functions in related ECUs through the operating process of CAV, which should be tested for accuracy and strength to support the requirements of the design, development, operation, and evaluation of the model. The requirements can fit together with standards (e.g., the working document ISO 21434 "Road Vehicles – Cyber Security Engineering") and functional safety requirements (e.g., ISO 26262 "Road vehicles - Functional safety") within the North American regulatory structure and utility requirements.

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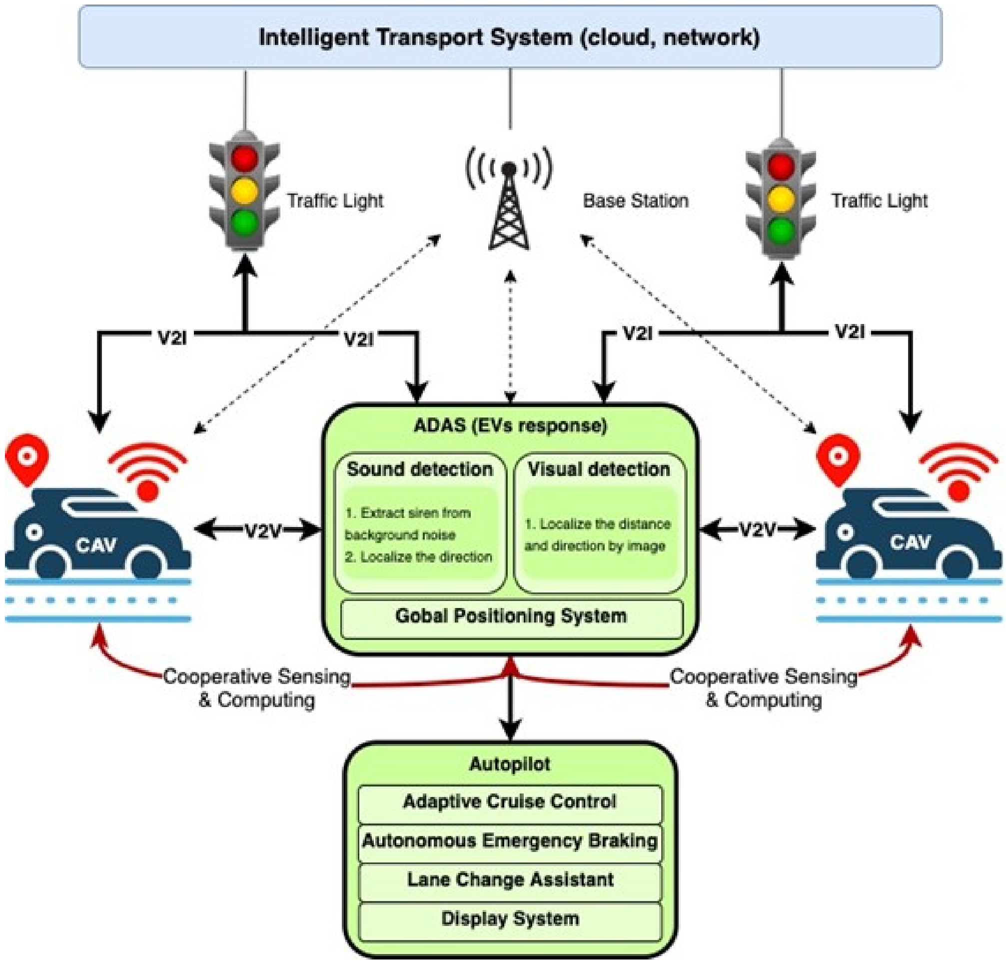

Figure 2: Conceptual Cooperative CAV System.

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