SEEING BEYOND THE

CONTROLLING CONNECTED AUTOMATED VEHICLES

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During the last two decades, auto manufacturers and technology companies have been developing vehicles with high levels of automation. Many advanced driver assistance technologies have already been made available on production vehicles while OEMs are still working toward full automation. In the meantime, a new generation of vehicle-to-everything (V2X) wireless communication technologies have been introduced to allow vehicles to share information with each other and with the fixed infrastructure. Merging connectivity and automation has large potential benefits for safety, fuel economy, and traffic efficiency but it also poses many challenges for vehicle control design. In this article, we discuss some past, present and future research on connected automated vehicles and their impact on road transportation. We also describe some specific algorithms and show the related experimental results to highlight the benefits of using beyond-line-of-sight information in real-world traffic systems.

BRIEF HISTORY OF VEHICLE AUTOMATION AND CONNECTIVITY

The last few decades have witnessed increasing automation of automobiles and heavy-duty vehicles. From the 1980s, microcontrollers started to penetrate production vehicles through various subsystems such as engine control units, anti-lock braking systems, etc. Soon the need for different microcontrollers to communicate with each other led to the invention of the controller area network (CAN) bus. In the 1990s, we started to see the appearance of on-board sensors that were used to monitor the environment and the motion of neighboring vehicles. These sensors, combined with more powerful computers, allowed vehicles to perform lateral and longitudinal control such as lane keeping and car following. Some of these efforts culminated in demonstrations such as the 1997 California PATH experiment in which eight automated vehicles were driven from Los Angeles to San Diego using a dedicated highway [1]. These technologies started to appear on high-end production vehicles in the late 1990s and early 2000s. In the meantime, with more powerful on-board

LINE OF SIGHT –

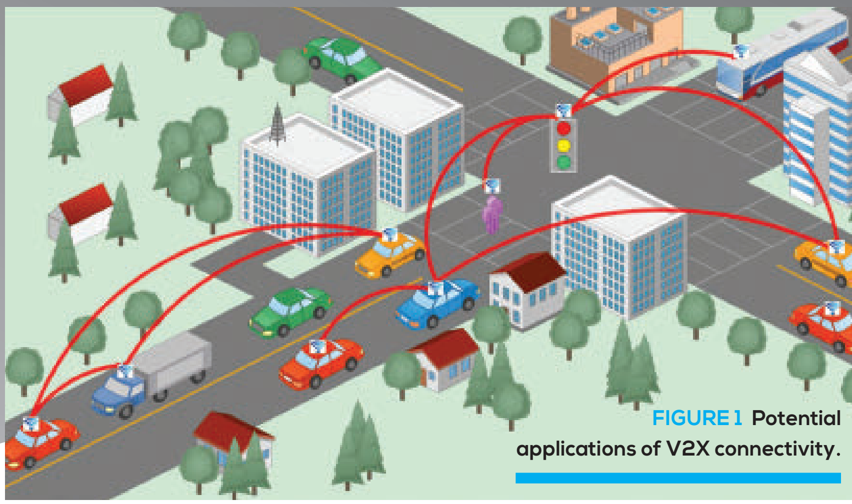

FIGURE 1 Potential applications of V2X connectivity.

computers and sensors such as GPS, lidar/radar, and cameras, researchers started to push toward higher levels of autonomy. These efforts were stimulated by events such as the DARPA Grand Challenges, where vehicles were given the task to drive autonomously in complex environments [2]. During the past decade, most major auto manufacturers have been investing in vehicle automation with the final goal of developing self-driving vehicles [3], while legislators have been making efforts to create an environment where such innovations thrive [4].

Starting from the mid-2000s, wireless communication technologies such as WiFi and 4G/LTE have been adopted in order to facilitate vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication. These are often referred to as vehicle-to-everything (V2X) communication, where X also includes pedestrians, bicyclists, etc. In particular, in the US, dedicated short range communication (DSRC) has been standardized based on IEEE 802.11p protocol, which allows low-latency, ad-hoc, peer-to-peer communication with 10 Hz update frequency. Moreover, message sets such as the basic safety message (BSM) and the signal phase and timing (SPaT) message have been standardized during the last half decade. A set of new technological vendors have been developing and manufacturing on-board and roadside units, allowing the creation of V2X-based safety applications that warn drivers about impending dangers [5, 6]. These include V2V applications such as forward collision warning, blind spot warning, intersection movement assist and V2I applications such as red light violation warning, curve speed warning, and weather condition warning; see **Figure 1**. Most of these applications can be realized based on BSMs (that contain GPS position, speed, heading angle, and yaw rate) and SPaT messages, while customized information (such as pedal positions in the CAN data) may also be sent utilizing the WAVE short messages protocol (WSMP). Warnings can be communicated to the driver using visual, auditory or haptic cues. Due to the human limitations in processing a large amount of information within limited time, it is desirable to use computers to process and aggregate information. The synthesized control actions may be suggested to the driver or executed by an automated system.

CONNECTED AUTOMATED VEHICLES IN HUMAN-DRIVEN TRAFFIC

During the past five years, automated driving technologies have progressed through many milestones, such as accumulating millions of miles in real-traffic testing. While the driving automation is learning to deal with more complex environments, there remain a considerable number of disengagement incidents, where an automated vehicle is unable to safely navigate the traffic and calls for human intervention [7]. It is not only difficult to eliminate such disengagements, but also difficult to ensure safe human take-over, because current on-board sensors need higher reliability, more redundancy, and larger perception range [8]. For example, radar/lidar and cameras may be able to obtain the distance of a vehicle within the line of sight, but they often cannot provide information such as the heading angle or yaw rate [2]. This may lead to difficulties in predicting and tracking the motion of surrounding vehicles, and such difficulties have been observed to trigger disengagements of automated vehicles at intersections and highway ramps [7]. Similarly, many disengagement incidents happen due to non-ideal weather/road conditions where the sensors could not determine the color of traffic lights or the position of lanes.

Aside from limited information type and working conditions, the most fundamental limitation on-board sensors face is the line of sight: they cannot see through an obstructing object or see around a blind corner. This gives an automated vehicle a confined view of its surroundings, which can impact the safety margin of its driving strategies. Thus, it is desirable to equip an automated vehicle with V2X communication so that it utilizes information both within and beyond its line of sight for decision-making and motion-control. We refer to such a vehicle as a connected automated vehicle (CAV).

V2X connectivity can greatly enhance the capability of automated vehicles to perceive their environment. Connected automated vehicles are able to see around a blind corner when moving toward an intersection, and know whether any vehicle is approaching from other directions. They can see through dozens of cars when a car several hundred meters ahead is skidding on ice or applying harsh braking, and decide how to avoid the safety hazard [5, 6]. Even information within the line of sight available via sensors can be augmented by V2X connectivity. For example, a connected automated vehicle can obtain accurate heading angle and yaw rate from BSMs transmitted by a neighboring vehicle, and determine with higher confidence whether the other vehicle is turning or changing lanes. Similarly, a connected automated vehicle can obtain from SPaT

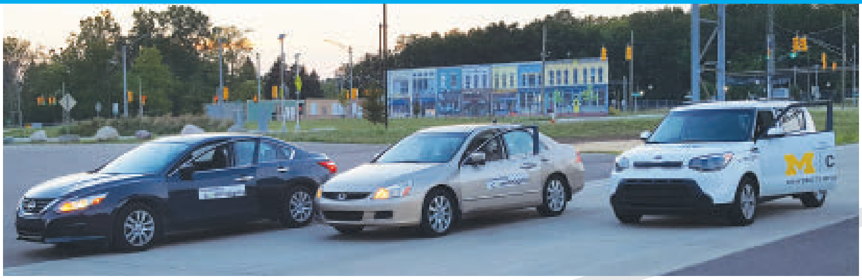

FIGURE 2 Two connected (left and middle) and a connected automated vehicle (right).

messages not only the exact color of the traffic lights, but also when the lights will change, which may help it to decide how to approach an intersection [9]. Perceiving events within and beyond the line of sight allows a connected automated vehicle to build up clairvoyance, so that it responds to situations earlier, makes better decisions, and avoids hazardous scenarios.

Because of the benefits that V2X connectivity promises, we are expecting a rapid increase in the penetration of V2X communication devices in the near future. On the vehicle side, multiple automakers are equipping new production vehicles with on-board units facilitating V2V and V2I communication, since the added cost is very small compared with the potential benefits [10-12]. On the infrastructure side, multiple US cities are piloting the deployment of roadside units [13, 14], while countries like Japan have already built such infrastructure in multiple areas.

Given the rapid expansion of V2X technology and the ambitious self-driving timeline from many automakers, a future where all vehicles are connected and automated seems within reach. Researchers are already designing sophisticated controllers for CAVs to cruise the highway in platoons [15-20] or cross intersections with no traffic lights [21-23]. However, as V2X devices and higher-level driving automation gradually penetrate the market, early generations of CAVs will need to operate in traffic systems where most vehicles are human-driven and only a fraction of those are equipped with V2X devices. Then a key question to answer is how connectivity can be utilized by a CAV so that it improves its own performance as well as the performance of the neighboring human-driven vehicles. This would lead to a paradigm shift in how we design the motion-control and decision-making algorithms: instead of passively responding to traffic perturbations created by human drivers, a connected automated vehicle may actively mitigate undesirable traffic behaviors propagating through the traffic flow.

LEARNING, ADAPTATION, AND CONTROL OF CAVS

By augmenting sensory information with V2X communication, connected automated vehicles are able to build up detailed knowledge of their driving environment and create data-based models for estimation, prediction, and control. However, a CAV needs to identify the constantly-changing configuration and driving behaviors of neighboring vehicles to be clairvoyant in real traffic. Such identification can be quite challenging, because a particular vehicle may only appear within the sensors' line of sight for a few seconds, and V2X information may not include every vehicle nearby. While algorithms based on a first-principle model can be used to identify the configuration of surrounding traffic, combining these with data-based methods may significantly enhance the robustness of estimation [24]. Similarly, in order to better describe and predict human driving behavior, important human parameters including driver reaction time can be identified using real-time V2X information [25]. Knowing the driving behavior of neighboring vehicles helps the CAV to adapt to different traffic environments, so that it can be better accepted by its human passengers as well as other road users.

While V2X communication allows connected automated cars to be clairvoyant, it also brings interesting challenges into decision-making and controller design through the highly-dynamic environment of vehicular traffic. For example, a connected automated vehicle and nearby human-driven vehicles (some of which are equipped with V2X devices) form an ad-hoc connected vehicle system that has time-varying configuration and network topology. Thus, a connected automated vehicle needs to be robust against uncertainties in the driving behavior of neighboring vehicles as well as against stochastic packet drops in wireless communication [25, 26]. Moreover, connectivity-based control algorithms need to be scalable and flexible, so that the macroscopic performance of a connected traffic system keeps improving as the penetration rate of V2X-equipped vehicles and connected automated vehicles increases [27]. In order to achieve this, one may identify beneficial motifs in vehicular networks and design connected automated vehicles to facilitate the formation of such motifs [28]. In particular, as the size of a connected vehicle system increases, algorithms with low computational costs will be needed to allow adaptation of connectivity topology with the limited sojourn time of V2X signals [29].

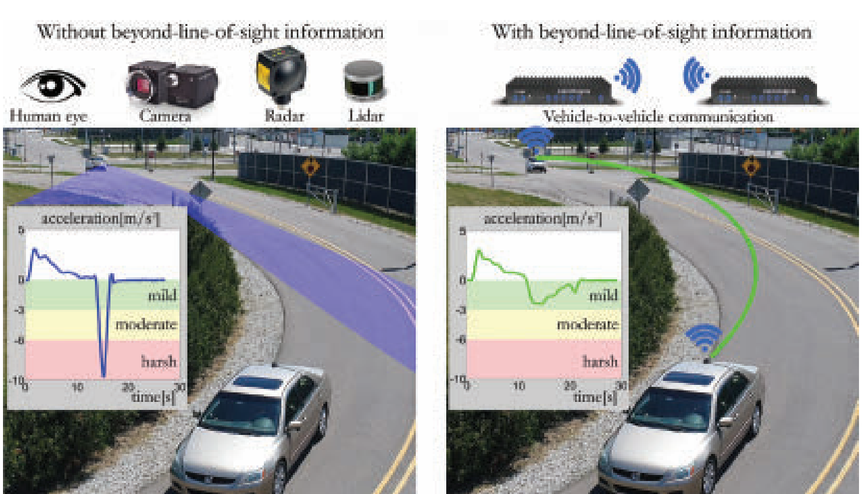

FIGURE 3 Comparison of the behavior of a vehicle approaching a stationary vehicle.

IMPROVING SAFETY AND EFFICIENCY OF TRAFFIC FLOW WITH CAVS

In order to demonstrate the benefits of utilizing beyond-line-of-sight information, we

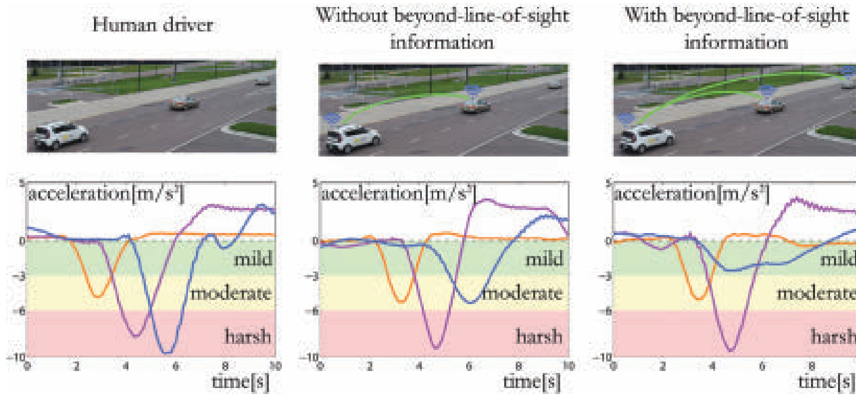

FIGURE 4 **Comparison of the behavior of a vehicle responding to a braking cascade.**

carried out a series of experiments using a connected automated vehicle that responded to the motion of multiple human-driven vehicles equipped with GPS and DSRC devices; see **Figure 2**. The results below show that connectivity, when utilized appropriately, may significantly improve the safety and efficiency of the CAV and the human-driven vehicles around it [30].

The first experiment is summarized in **Figure 3**, where a vehicle is approaching another vehicle stopped along the road. Due to the road geometry and elevation, the stationary vehicle only appears within the line of sight when the distance between the two vehicles is around 25 meters. Thus, harsh braking is required if the car was traveling close to the speed limit (35 mph). Indeed, a braking maneuver is recorded that reaches almost -10 m/s^2 (left panel of **Figure 3**). Such a deceleration not only adversely impacts passenger comfort, but may also lead to collisions under non-ideal road conditions. However, this potential hazard can be avoided when the line of sight of the human driver or on-board sensors (highlighted by the blue cones) is augmented by V2V information. In the right panel of **Figure 3**, the same scenario is handled by a connected automated vehicle that is aware of the stationary vehicle via V2V communication. In this case, its maximum deceleration only reaches -2 m/s^2, which would keep the vehicle safe even if the road surface was not ideal. We note that the connected automated vehicle starts braking when the stationary vehicle is around 70 meters away, well beyond the line of sight.

The second experiment is summarized in **Figure 4,** where three vehicles follow each other on a straight road and the human driver of the first vehicle applies moderate braking (around -5 m/s^2). In response to this perturbation, the human driver of the second vehicle brakes more severely (around -8 m/s^2). The left column shows that when the third vehicle is also driven by a human driver, its deceleration reaches a hazardous -10 m/s^2. The middle column shows the response of a connected automated vehicle in the same situation without beyond-line-of-sight information. That is, the CAV only responds to the motion of the human-driven vehicle immediately ahead (as a sensor-based automated vehicle might do). Due to smaller response time and better accuracy, it brakes less harshly with a peak deceleration around -5 m/s^2. Finally, the right column shows the scenario when the connected automated vehicle utilizes beyond-line-of sight information and responds to the motion of both vehicles ahead. Its peak

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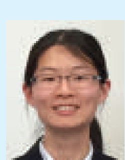
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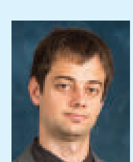
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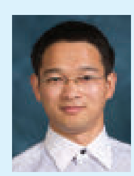
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deceleration is only -2.5 m/s^2, indicating better safety and passenger comfort.

While the two examples above demonstrate that a CAV can be made safer by beyond-line-of-sight information, the robustness and scalability of connectivity-based control algorithms are also being experimentally validated. For example, when a non-transmitting vehicle is between the two DSRC-equipped human-driven vehicles ahead, the CAV is able to maintain a similar level of improvement without changing its controller. Moreover, when utilizing information from larger numbers of transmitting vehicles ahead, the CAV is able to further enhance its performance. Apart from safety improvements, beyond-line-of-sight information may be used to intercept the cascading perturbations among human-driven vehicles and alleviate stop-and-go traffic jams. This benefit can be realized through connected automated vehicle designs that are "head-to-tail string stable" [26]. Such a design was used in the right column of **Figure 4**, where the deceleration of the connected automated vehicle (tail) exhibits even smaller amplitude than the human-driven vehicle (head). Aside from smoother traffic flow, better energy efficiency has also been observed during road tests among real traffic [31]. The multiple experimental studies all indicate the positive impact of CAVs on the efficiency of the road transportation system.

OUTLOOK FOR CONNECTED AUTOMATED TECHNOLOGY

The results discussed in this article are only a small fraction of connected automated vehicle research. Many other interesting problems are being studied, especially regarding more diverse driving environments such as multi-lane roads, highway ramps, and traffic intersections with pedestrians and bicyclists. In these complex traffic scenarios, individual vehicles and other transportation participants may benefit more from harnessing V2X connectivity in decision-making and motion control. With automation and connectivity technologies increasingly integrated and validated on road vehicles, the road transportation system is stepping into a safer, more economical, and more efficient future. ■

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A DRIVER'S LICENSE TEST FOR DRIVERLESS VEHICLES

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Autonomous vehicles (AVs) have already driven millions of miles on public roads, but even the simplest maneuvers such as a lane change or vehicle overtake have not been certified for safety. Current methodologies for testing of Advanced Driver Assistance Systems, such as Adaptive Cruise Control, cannot be directly applied to determine AV safety as the AV actively makes *decisions* using its perception, planning and control systems for both longitudinal and lateral motion. These systems increasingly use machine learning components whose safety is hard to guarantee across a range of driving scenarios and environmental conditions.

New approaches are needed to bound and minimize the risk of AVs to reassure the public, determine insurance pricing and ensure the long-term growth of the domain. So what type of evidence should we require before giving a driver's license to an autonomous vehicle? To answer this question, consider the major components which make up an AV. An AV is typically equipped with multiple sensors, such as a LIDAR (a laser range finder) and several cameras (**Figure 1**(1)). The readings of these sensors are processed by algorithms that extract a model of the current scene, like object detectors, in order to understand *who's doing what and where*. This information is then fused together to provide the AV with its state estimate, such as position and velocity, and that of the other agents in the scene. The AV must then decide where to go next (a discrete decision taken by the behavioral planner), what continuous trajectory to follow to get there (a computation performed by the trajectory planner) and how to actuate steering and acceleration to follow that trajectory (performed by the trajectory tracker). Add to this the interaction with other vehicles, changing weather conditions and the respect of traffic laws, and it is clear that verifying correctness of AV behavior is a gargantuan task.

WHOLE-AV TESTING

Such considerations have led AV researchers to *formal methods* to provide a high level of assurance. This term encompasses a wide field of theory, techniques and tools for answering the following question: Given a *mathematical model* of a System Under Test (SUT), and a *formal specification* of correct system behavior, does the SUT model satisfy the specification? A formal tool's answer is *complete and sound*[1]. If the SUT model is incorrect, the tool *will* find an example violation, also called a *counter-example*. And if the tool returns that "The model is correct", then the model is indeed correct and does not violate the specification. Unlike testing, there is no question of 'Could we have found a bug if we had tested more?'

Formal methods applied to the problem of AV verification

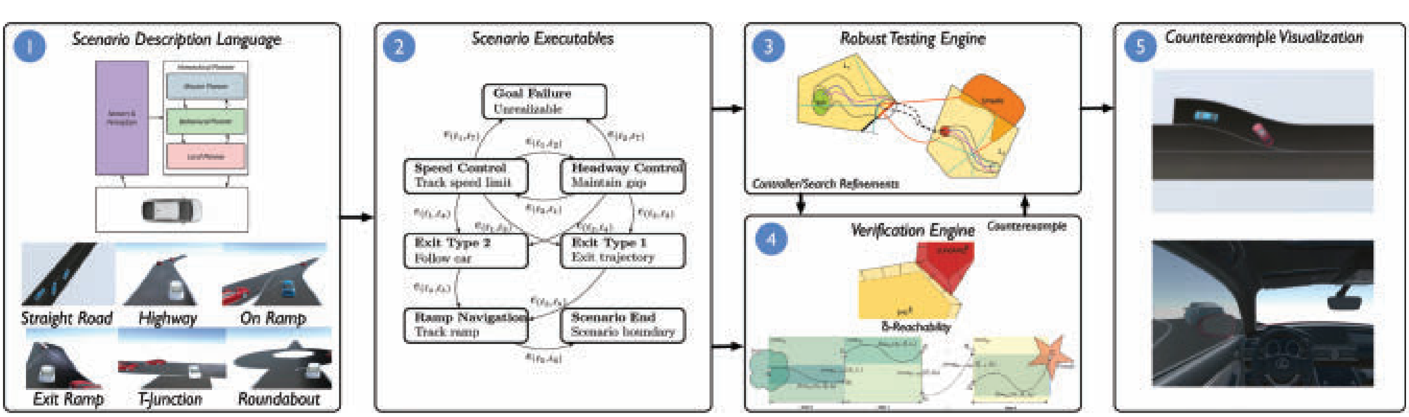

FIGURE 1 The AVCAD toolchain: (1) A Scenario Description Language allows quick creation of driving scenarios (2) The scenarios are translated into formats that can be processed by the testing and verification tools (3) Robust Testing [G. Fainekos] (4) Formal Verification Engine [S. Kong] (5) Requirement violations are visualized for an intuitive understanding of the violation.

[1] Though some provide approximate answers for more complicated models.