Collaborative Sciences Center for ROAD SAFETY

FINAL REPORT

Advancing accelerated testing protocols for safe and reliable deployment of connected and automated vehicles through iterative deployment in physical and digital worlds

Year 1 Report, June 7, 2020

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U.S. DOT Disclaimer

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16. Abstract

As Automated Vehicles diffuse through the transportation system, it is important to understand their safety performance. Although few AV-involved crashes have occurred on roads during testing, they pose new challenges and opportunities for improving safety. The challenges come from using complex automation technologies operating at high speeds to make lateral and longitudinal control decisions, increasing the chances of software and hardware failure. Are vehicles with lower or higher automation safe enough to drive on public roads, and more fundamentally, how do we assess their safety envelope? At the same time, there are opportunities to understand AV-involved crashes by leveraging newly available AV data. In this CSCRS project (reporting on Year 1 activities), we take steps toward developing testing procedures for connected and automated vehicles by using a novel software and physical deployment platform which allows rapid iterative development. With such procedures, automated vehicles can be systematically tested and in the future certified to be generally safe in addition to being tested on public roads. This study first conducts a review of literature, capturing AV-involved crashes, and the role of automation, followed by how AV cameras, LiDAR, and radar can assist greatly in identifying contributing factors, e.g., the manner of collision and whether the automated driving system was engaged. Two carefully selected AV-involved crashes in California are analyzed by simulating them and demonstrating the added value of AV sensors. This can assist in the identification of fringe cases and stress points where automated systems may be prone to collisions. In addition to simulating individual crashes, counterfactuals are developed by combining crashes—e.g., an AV rear-ended by a conventional vehicle as it stops for a jaywalking pedestrian. The sensors' performance (e.g., range and resolution) is also analyzed. The study demonstrates the role of AV sensors in safety. This can lead to safety certification standards in the future. This study applies the safe systems approach by showcasing and suggesting the need for AV testing protocols that can assist in safer operation of vehicles.

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1. Introduction

Vehicle automation is diffusing rapidly through the transportation system with low level automation vehicles (that assist drivers with control assists and technologies such as lane keeping and forward collision warning systems) commercially available. High levels of automation allow the vehicle to drive itself. These automation levels have been formalized by the Society of Automotive Engineers as ranging from Level 1 (low level of automation) to 5 (high level of automation). Currently, many manufacturers are marketing vehicles with Society of Automotive Engineers (SAE) Level 2 or 3 automation and testing with more advanced vehicles on public roads (Level 4). However, recent crashes of automated vehicles have raised critical questions about their safety (Boggs, Wali and Khattak, 2020): are vehicles with lower or higher automation safe enough to drive on public roads, and more fundamentally, how do we assess their safety envelope? Currently, there is no consensus about whether testing should exist at the state or federal level, what functions should be tested, how independent testing should occur, and what constitutes safe thresholds.

In this CSCRS project, we seek to address this gap by developing a comprehensive testing protocol specifically for Level 2 and 3 connected and automated vehicles by using a novel software and physical deployment platform which allows rapid iterative development. With such a testing protocol, automated vehicles can be systematically tested and certified to be generally safe for driving by the public or for further testing on public roads. There are four key objectives of this research:

1. Conduct a review of ongoing efforts on automated vehicle crashes and standards development.
2. Develop a testing procedure that can standardize how to systematically and safely test Level 2 and 3 automated vehicles regarding their functions and capabilities with considerations of the driver and environment settings. The procedures are designed to allow accelerated testing and identification of fringe cases and stress points, as reflected in AV crashes, where automated systems will be prone to failure.
3. Work toward providing safety certification standard recommendations that regulatory agencies at the state and federal levels and the private sector can use, if they so choose.
4. Involve stakeholders, i.e., government agencies and private sector companies, in CAV testing and enable discussion on safety and certification processes.

This report summarizes activities conducted in the first year of this project.

2. Current State-of-the-Art

With the increasing presence of semi-autonomous vehicles that leverage advanced driving assist systems as well as the promise of self-driving cars, ensuring their safety has become more and more challenging. Recent fatal accidents involving partially-automated driving systems (Boudette, 2016); (National Transportation Safety Board (NTSB), 2016); (National Transportation Safety Board (NTSB), 2020); (National Transportation Safety Board (NTSB), 2019); (National Transportation Safety Board (NTSB), 2018) as well as a number of high-profile non-fatal accidents (National Transportation Safety Board (NTSB), 2018); (Winkler, 2018); (Siddiqui, 2019); (Templeton, 2020) have drawn heightened awareness of the need for more thorough testing and certification of these vehicles. Themes common to all of these incidents include driver distraction and overreliance on the automated capabilities, highlighting the significant need for a robust Driver Monitoring System (DMS) in these platforms.

Failures in these systems and inadequate designs have been significant contributors to many of the accidents. For example, in a fatal Tesla crash in Williston, Florida involving the vehicles “Autopilot” feature, the driver operated the controls for only 26 seconds out of an over 37 minute long trip and missed or ignored 6 out of 7 alerts presented by the system requesting that they operate the steering wheel. Similarly, in an incident in Tempe, Arizona where an automated Uber test vehicle struck and killed a pedestrian, the vehicle failed to alert the distracted backup driver to the impending collision until 1 second prior to impact, at which point there was not sufficient available time for takeover (National Transportation Safety Board (NTSB), 2018).

Inadequate driver monitoring systems have come under scrutiny in cars with advanced driving assist systems. For example, in a recent report analysing a fatal crash involving a Tesla vehicle operating on Autopilot in Mountain View, California, the NTSB explicitly concluded that the vehicle's system of monitoring driver-applied torque on the steering wheel was insufficient to determine whether the driver was adequately engaged with the driving task (National Transportation Safety Board (NTSB), 2020).

Despite such problems, regulation of driver monitoring systems has been minimal. The New Car Assessment Program (NCAP), a consumer information program for evaluating vehicle safety performance managed by the National Highway Traffic Safety Administration (NHTSA) does not cover driver assist features, limiting its assessment to collision and rollover survival (National Highway Traffic Safety Administration (NHTSA), 2018). The Insurance Institute for Highway Safety (IIHS) covers some advanced driver assist system (ADAS) features such as pedestrian detection and automated emergency braking (AEB) but does not address driver monitoring (Insurance Institute for Highway Safety (IIHS)). The European NCAP has a similar scope, covering speed assistance, AEB, and lane-keeping but has announced that it will begin assessing driver monitoring in the 2022 revision of its protocols (The European New Car Assessment Programme (Euro NCAP)).

The Korean Ministry of Land, Infrastructure, and Transport (MOLIT) is the only major authority regulating driver monitoring (Ministry of Land Infrastructure and Transport (MOLIT)). Beyond requiring that partially-automated vehicles including some type of DMS, MOLIT provides guidelines on how driver inputs should trigger engagement and disengagement of the automated system and explicitly specified the types of allowed modalities for assessing driver engagement. Such states can include either input to vehicle controls, intentional head or body movement, or the absence of recent eye closures.

MOLIT also reduces transition times for the human to resume control compared to Teslas. For example, in some cases if a human does not immediately respond to a request for handover from the computer, the system will take action within 10 seconds to actively slow the car with the ability to bring the car to a halt. Such a situation in an Autopilot-equipped Tesla can require 30 seconds or more for a driver's response.

In terms of standards for driving assist and driver monitoring, only a limited set exist that address the development of new testing frameworks and certifications. The most directly applicable standard is UL 4600, which addresses the development of safety cases which are evidence-based claims about what the autonomous vehicle can and cannot safely do. It covers topics related to design, verification and validation, and life cycle management, though the standard itself is much less prescriptive on specific content than previous standards (i.e., it does not enumerate the types of hazards that must be addressed, leaving that to the judgement of the technology developer) (Underwriters Laboratories (UL)).

Other standards with relevance to DMS certification are SAE J3016, which defines the levels of autonomy in vehicles (Society of Automotive Engineers (SAE) International, 2014); ISO 26262, which covers functional safety but not specifically targeted at vehicle automation (International Organization for Standardization (ISO)); and ISO 21448, which addresses safety of the intended functionality for systems requiring both a high degree of situational awareness and complex computer reasoning or synthesis of sensor data (International Organization for Standardization (ISO)).

Efforts to develop more rigorous approaches to certification of autonomous systems like DMS in the academic community have paralleled those in industry. Several theoretical challenges exist to verifying and certifying the behavior of inherently "black box"-like systems such as the artificial neural networks used in many autonomous platforms (Kurd, Kelly and Austin, 2007). Even the state-of-the art in current testing practices may fail for these types of systems as these approaches do not sufficiently verify the behavior of autonomous systems in all the possible scenarios in which they may operate. They also do not provide sufficient assurance that such systems can safely undergo thorough testing in real operational domains (i.e., in settings where they may interact with the public).

Some new research is attempting to address these gaps. For instance, several studies have demonstrated the use of various model checking frameworks for validating the behavior of automated components used in aircraft and underwater vehicles. Arithmetic verification, a derivation of model checking, has been evaluated for use with autonomous vehicles as well (Althoff, Stursberg and Buss, 2007).

Although these techniques show some promise, they have several limitations which restrict their practical use for systems with more complex behavior. First, approaches that rely exclusively on computationally-intensive numerical simulation assume a finite decision-making space and thus, require a heavily simplified model of the autonomous system and its operational domain (Webster et al., 2011); (Alexander, Hall-May and Kelly, 2007); (Fisher, Dennis and Webster, 2013). For example, to validate the performance of an autonomous driving system, one group simplified the vehicle's dynamics from differential equations to a simple Markov chain, removing most interactions with the environment, and assuming all other vehicles were law-abiding and non-adversarial (Kurd, Kelly and Austin, 2007). Assuming such an "ideal" case excludes the vast majority of safety-critical scenarios.

Another issue is that autonomous systems increasingly rely on probabilistic modeling, AI, and machine learning (ML), and the behavior of such systems cannot be described deterministically (Alexander, Hall-May and Kelly, 2007); (Fisher, Dennis and Webster, 2013); (Bhattacharyya et al., 2015). This issue can be partially addressed through the validation of the data used to train these algorithms (Brat et al., 2006) or by extrapolating the results of one verification test to other untested scenarios via advanced statistical methods (Alexander, Hall-May and Kelly, 2007). However, for systems that use ML to evolve their behavior over time, it is not possible to validate all of the potential inputs or scenarios the system might encounter. Furthermore, certification relies on detailed documentation of the behavior of system components, and commonly used AI techniques such as deep neural networks have non-explainable intermediate layers whose behavior cannot be accurately characterized.

A third significant drawback is these approaches do not consider human-factors issues. Most "autonomous" systems do not function strictly autonomously and in fact usually function as a team alongside one or more human operator (e.g., an aircraft's autopilot system that co-operates with the human pilot, or a car's driver assist system that co-operators with the car's driver). An automated system that is functioning as intended may still produce behavior which the operator does not expect, resulting in a safety hazard, or it may induce the operator to use the system in an unsafe way (Endsley, 1999); (Parasuraman, Sheridan and Wickens, 2000); (Kaber, 2018); (O'malley, 2007). Any autonomous system certification framework for a self-driving system that requires a human to take control at any point in any operational domain will need to evaluate not just the technical performance of the autonomous system, but also the environmental and operator characteristics that influence how the system is used and the resultant safety outcomes.

3. Framework, Hardware, & Software

As mentioned, one of the purposes of this project is to develop a series of testing and validation protocols for SAE Level 2 and 3 automated vehicles that can potentially provide insight into automated vehicle performance, supplementing public on-road testing. We decided to focus on Level 3 automation, as it represents a higher level of challenge. The workflow is shown in Figure 1. To accomplish this, there are two key development and research avenues. First, a testing platform is needed to accurately measure vehicle performance in a virtual simulation, offering the research team the ability to test a variety of situations quickly and safely. This is being accomplished with both a combination of open source and licensed software, as well as access to hardware provided by the National Transportation Research Centre at the Oak Ridge National Laboratory. Second, this testbed must be leveraged to produce a quantitative approach to generating safety and validation metrics that encompasses both current government standards, as well as knowledge regarding vehicle hardware and software.

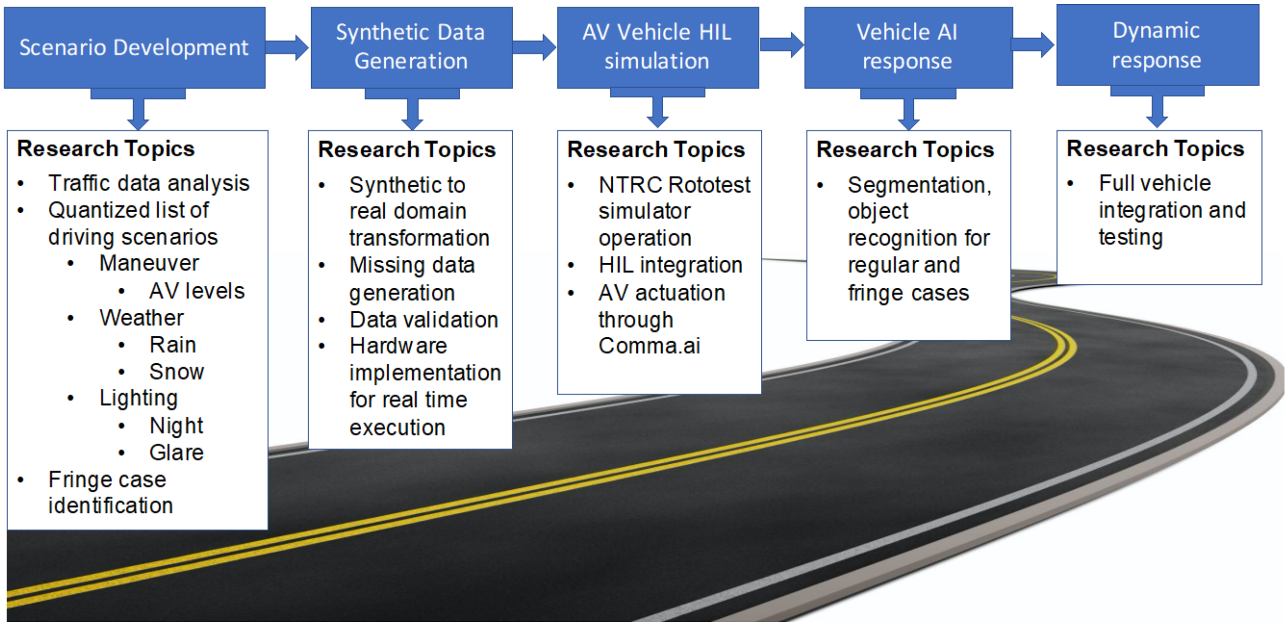

Figure 1: Workflow and roadmap of the project.

Notes: Selected scenarios with varying levels of automation are run through simulation to produce output in the form of Artificial Intelligence response and vehicle dynamics. Real world data generated through comprehensive testing by our partners in Duke University is used to train and validate the synthetic data generated in simulation. This information is used to compute a safety and performance metric for evaluation. At that point, a systematic approach can be used to cluster similar scenarios and ultimately produce a comprehensive approach to safety evaluation.

Simulation of automated vehicles would not be possible without access and proficiency with a variety of software and hardware made specifically for that purpose. An abbreviated list of tools currently available and being implemented on this project are shown below:

- **CARLA:** Open source automated vehicle simulator created and sponsored by Intel.
- **SUMO:** Open source, highly portable, microscopic and continuous multi-modal traffic simulation package designed to handle large networks. Furthermore, VENTOS VEhicular NeTwork Open Simulator can also be used along with SUMO.
- **TENA:** Test and Training Enabling Architecture that provides interoperability for integrated testing and simulation in large-scale real-time synthetic environments.
- **dSpace MotionDesk:** Licensed vehicle simulator with similar objective as CARLA, containing many features for Hardware in the Loop (HIL) simulation.
- **Unreal Engine 4:** Graphics engine platform providing low level tools for simulation that is the basis of CARLA.
- **RoadRunner:** Commercial software made by *VectorZero* for producing custom maps, roads, and driving scenarios in collaboration with CARLA.
- **Automated Driving Toolbox (MATLAB):** Set of tools for designing and analyzing self-driving systems.
- **Autoware:** A collection of lower level API's intended to take sensor input and perform AV tasks such as localization, planning, and control.
- **Drive PX2 (NVIDIA):** GPU oriented computer intended to perform real time image processing on-board an autonomous vehicle.
- **Comma two (comma.ai):** Intermediate hardware that allows users to access vehicle information from the CAN bus of a car and control various aspects of the driver assistance systems.

- **KITTI, NuScenes, & Waymo:** Various datasets that were specifically formed for autonomous vehicle research. They can be (and are being) used for machine learning related objectives.

This is not an exhaustive list of the hardware and software being implemented by the team. It is simply a demonstration of the wide scope of industry tools that are being used by the team to accomplish the goals laid out in the road map. Below is a detailed summary of the road map laid out in Figure 1.

4. Development of Safety Test Scenarios for AVs

4.1. Text Mining on Existing AV Crash Reports

Before developing safety test scenarios for AVs, information contained in AV crashes was extracted to understand the context in which AV crashes have occurred. The California Autonomous Vehicle Tester Program provides a rich resource of AV involved crashes. Text mining analysis was conducted on AV crash narratives in order to explore influential factors affecting AV crashes. The crash reports available are from 130 AV crashes in California from January 2019 to June 2020 (California Department of Motor Vehicles). Figure 2 shows the "Word Cloud" representing the keywords visually. Larger sized words appear more frequently in crash reports. As expected, "AV," "Vehicle," and "Autonomous" are the most frequent words.

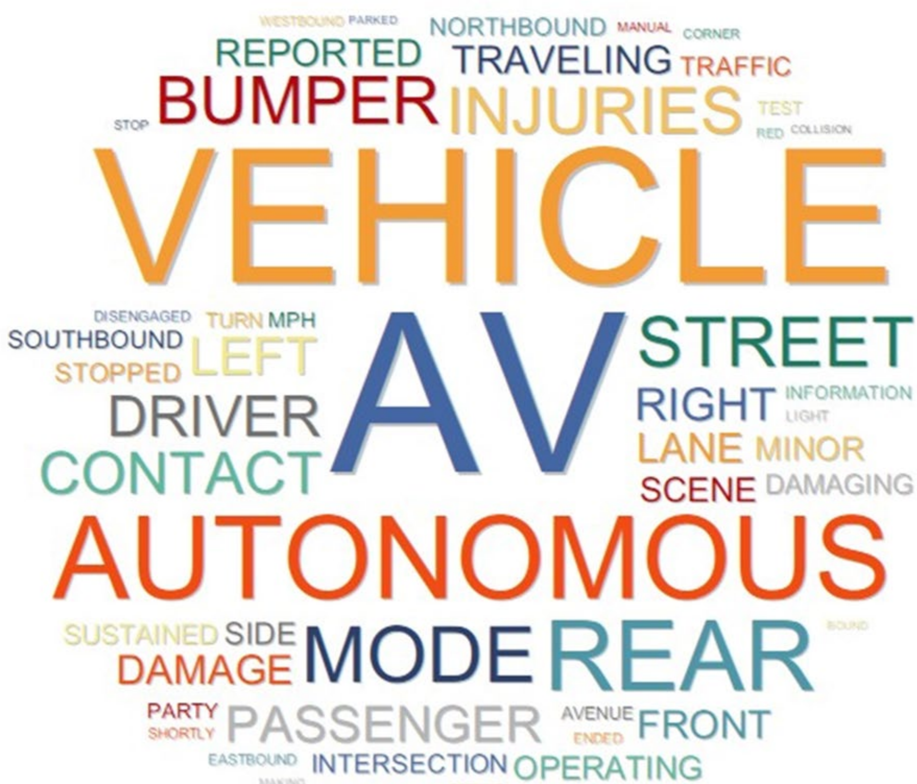

Figure 2: Word Cloud from Text Mining on AV Crash Reports in California

The text mining of crash narratives provide factors that can be considered when structuring safety test scenarios. First, regarding roadways, streets including intersections are critical for AVs because they are more likely to be rear-ended by conventionally driven vehicles. Additionally, expressways including ramps and interchanges (where margining happens) are also critical for AVs. Concerning road users, it seems crucial for AVs to interact with bicyclists and motorcyclists as well as surrounding vehicles. Moreover, among driving tasks, making a left-turn or right turn were highly related to AV involved crashes. Furthermore, keywords in the narratives, such as “Rear,” “Bumper,” and “Front,” suggest that AVs’ performance to keep a safe distance from vehicles in the rear is important. More analysis of the AV-involved crash narratives and variables in the reports is on-going.

4.2. Safety Test Scenarios for AVs

Hardscapes in the form of roads, buildings, trees, crosswalks, stop signs and other civic structures, which will be important for testing safety performance of computer vision algorithms under partial occlusion, road surface degradation, etc. were conceptualized. Weather and visibility, rain, snow, day/night, light and long shadows, stark reflections and glare, etc. are elements that form complex driving environments. The scenarios of safety test for automated vehicles have been established on the operational design domains (ODDs) structured with the dimensions of roadway, traffic condition, and environmental condition as suggested by Thorn et al. (Thorn et al., 2018). For every single domain with specific roadway type, traffic condition, and environmental condition, corresponding tasks including tactical maneuver behaviors and detection and response behaviors are assigned to AVs in the test. The scenarios consist of 100 domains in total and each domain includes appropriate tasks for AVs. The dimensions of relevant features are discussed in detail below.

Dimensions of Roadways

Roadways can be categorized by their classification and types. First, based on their classification, roadways are classified into three categories including local roads, highways or collectors, and freeways/interstates or major arterials (as shown in Figure 3). Based on early AV testing in California, Boggs et al. have found that disengagements by test AVs has occurred most frequently on highways (collectors), freeways or interstates than on local roads (Boggs, Arvin and Khattak, 2020). Second, based on the types of segments, roadways can be classified into five categories including straight segment, curved segment, intersection, ramp, and directional interchange (as shown in Figure 3). Ramp and Directional Interchange are included only in the road classification of freeways or interstates while Intersections are not included in freeways or interstates.

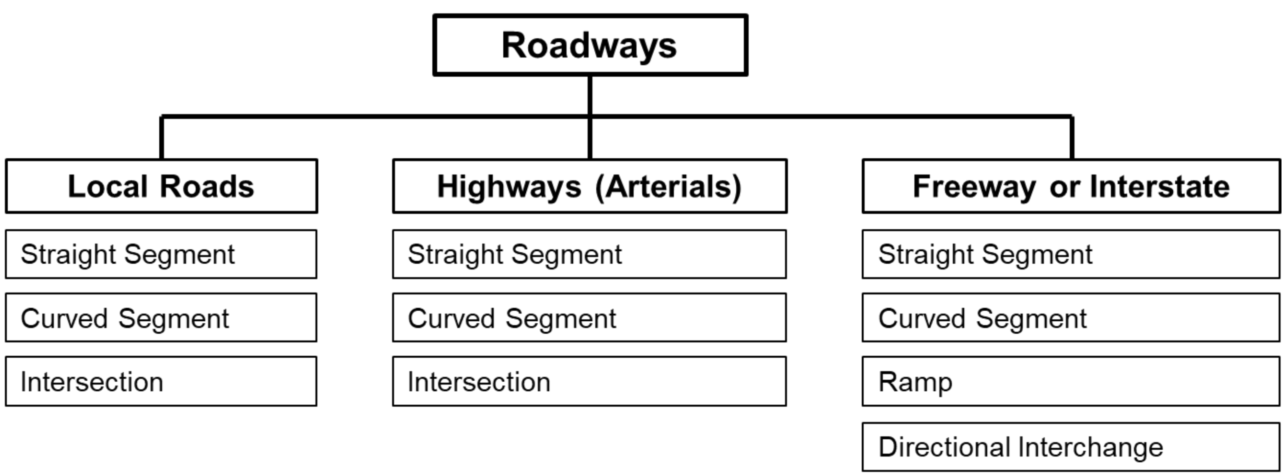

Figure 3: Dimensions of Roadways in Safety Test Scenarios

Dimensions of Traffic Conditions

Traffic conditions for AVs can be set as shown Figure 4, which can be divided into three main categories. While the first category is the condition where an AV drives alone on the road, the second one is the condition where an AV needs to interact with one conventional vehicle or another AV. A third category is the condition where an AV should drive in traffic stream with multiple vehicles, which can be conventional or Avs. The traffic stream can be further subdivided based on the penetration rate of Avs. Also, Avs can be in a Cooperative

Adaptive Cruise Control (CACC) platoon. Related research is reflected in several publications. Specifically, the team has recently published a paper on the impacts of ACC and CACC (Mahdinia et al., 2020). The paper uses real-world ACC and CACC data from a federal test to study their impacts on safety and other transportation performance measures. Specifically, CARMA data collected by the FHWA, U.S. DOT are used in this study. Another paper explores the role of Avs in mixed traffic environments interacting with conventional human-driven vehicles. The study uses field data collected in Texas (Mahdinia, Mohammadnazar and Khattak, 2020). Furthermore, the team has worked on optimal coordination control systems for connected vehicles at highway on-ramps (Han et al.); (Jing et al., 2019). The paper develops an optimal coordination algorithm to improve the safety, energy consumption and the environment.

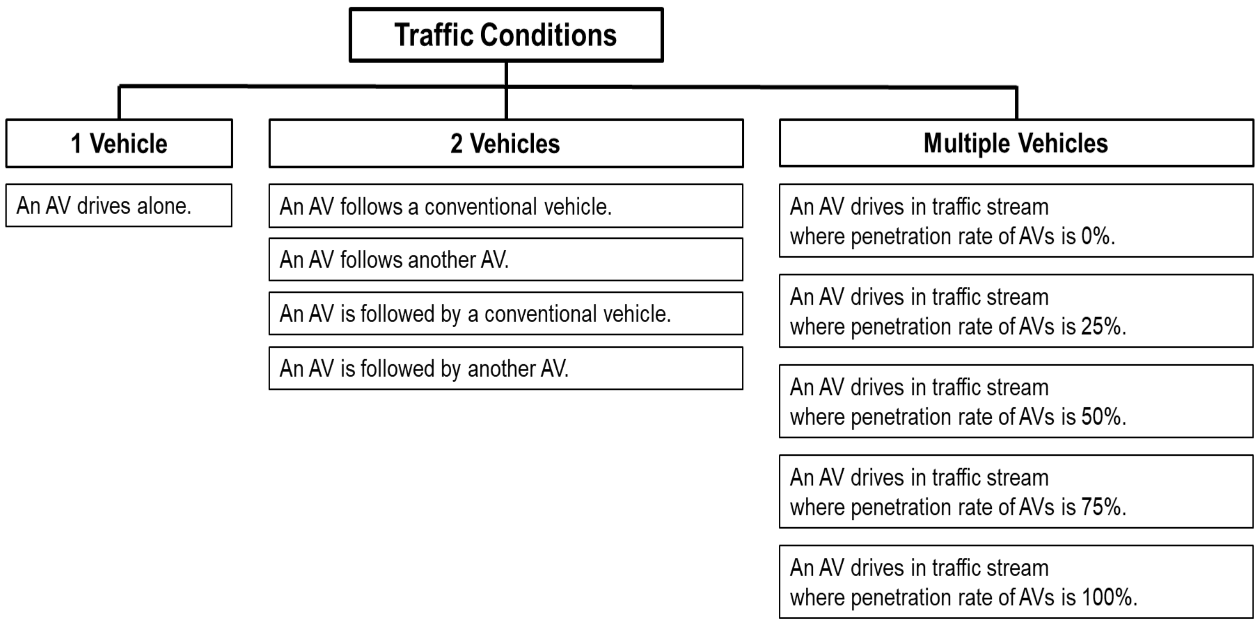

Figure 4: Dimensions of Traffic Condition Test Scenarios

Dimensions of Environmental Conditions

Environmental conditions for Avs can have a wide range as shown in Figure 5. Light conditions can be divided into day and night (and dawn/dusk) while weather conditions can be categorized as clear, rainy, snowy, and foggy weather (with finer categories possible). Each condition could be further subdivided such as light rain, moderate rain, and heavy rain depending on the resolution of simulation.

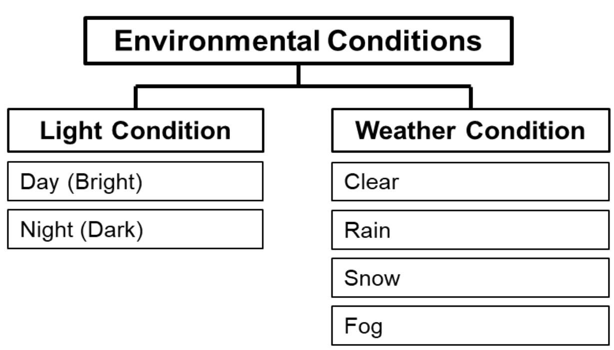

Figure 5: *Dimensions of Environmental Conditions in Safety Test Scenarios*

Driving Tasks

Suppose an AV is to perform driving tasks on specific roadway types and in certain traffic conditions. The following tasks shown in Figure 5 can be envisioned, based on the testing items for driver's license tests across the United States (Automating Government Services, https://yogov.org/dmv). For each domain with specific roadway type, traffic condition, and environmental condition, appropriate tasks can be assigned. The tasks are categorized by the SAE levels of automation (Society of Automotive Engineers (SAE) International, 2019) mentioned in Figure 6. While the main scope of this project is focused on automation levels 2 and 3, the driving tasks falling under levels 4 and 5 have been conceptually included in the scenarios.

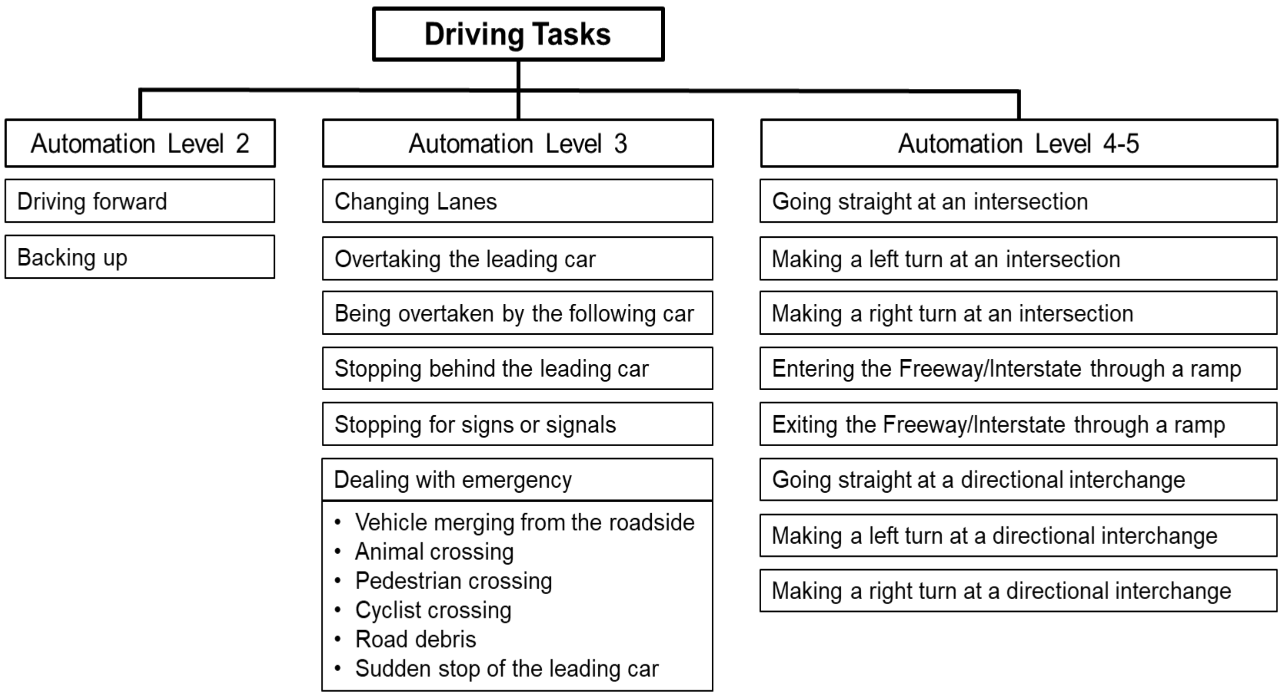

Figure 6: *Driving Tasks for Avs in Safety Test Scenarios*

Regarding unexpected or emergency situations, several types of such situations were categorized based on the most frequent harmful events leading to incidents or crashes (National Highway Traffic Safety Administration (NHTSA)). In order to assess how safely a task is performed, the performance of Avs can be quantified by surrogate safety measures such as driving volatility (Wali and Khattak, 2020), time to collision (TTC), lateral offsets to travel lanes, perception-reaction time, and success rate of avoiding a crash.

10.3. Fringe Case Identification

While some cases in the scenarios are not difficult to realize in real environments, other cases with dangerous or complicated situations are unsuitable to realize through on-road testing in terms of the safety of testers, cost, and physical constraints. For these cases, according to Koopman and Wagner (2018), simulation test can be a useful method to increase controllability as well as safety by avoiding physical world randomness and constraints (Koopman and Wagner, 2018). Thus, it will be desirable to conduct both simulation and on-road testing for safe or simple cases in the scenarios, which makes it possible to calibrate the parameters in simulation to reduce simulation inaccuracies. On the other hand, for dangerous or complicated cases, it will be desirable to conduct only simulation with the parameters pre-calibrated in safe cases.

For efficient tests, it is necessary to identify fringe cases, or edge cases, that consists of the most extreme conditions for Avs. Fringe cases have been identified with the combinations of driving task to deal with emergency and adverse environmental conditions including rainy night, snowy night, and foggy night as shown in Table 1 with part of safety test scenarios for Avs. The whole set of scenarios are provided in the Appendix.

Table 1: Example of Safety Test Scenarios for Avs with Fringe Cases

Night *, Rainy Weather *		An AV drives alone	An AV follows a conventional vehicle.
Local Roads	Straight Segments	Driving forward	Driving forward
		Changing lanes	Changing lanes
		-	Overtaking the leading car
		Backing up	-
		-	Stopping behind the leading car
		Stopping for emergency	Stopping for emergency
		Vehicle merging from the roadside *	Vehicle merging from the roadside *
		Animal crossing *	Animal crossing *
		Pedestrian crossing *	Pedestrian crossing *
		Cyclist crossing *	Cyclist crossing *
		Road debris *	Road debris *
		-	Sudden stop of the leading car *
	Curved Segments	Driving forward	Driving forward
		Changing lanes	Changing lanes
		-	Overtaking the leading car
		-	Stopping behind the leading car
		Stopping for emergency	Stopping for emergency
		Vehicle merging from the roadside *	Vehicle merging from the roadside *
		Animal crossing *	Animal crossing *
		Pedestrian crossing *	Pedestrian crossing *
		Cyclist crossing *	Cyclist crossing *
		Road debris *	Road debris *
		-	Sudden stop of the leading car *

Notes: The cases with * are the fringe cases.

5. Synthetic Data Generation

Synthetic Sensor Data Generation is the task of producing synthetic data under simulation that has the characteristics of real data that might be collected on an actual vehicle driving on public roads. Automated vehicles carry sensors such as lidar, radar, and cameras. To realistically simulate an automated vehicle, the performance data must be reproduced in a way that includes some level of noise and other factors that are situation dependent. We are approaching this problem of producing realistic data using a variety of methods. Through this project, we are using our access to powerful computers intended for Hardware in the Loop or HIL simulation that can physically simulate various types of sensors in real time. We are also using a variety of machine learning and sensor fusion techniques that can intelligently be used to accomplish synthetic data generation, especially capturing the edge or fringe case scenarios. The current goals related to this task being investigated are discussed below.

5.1. Synthetic-to-real domain shift:

There will always be a fundamental difference between synthetic sensors and real sensors in terms of the method of operation, environmental resolution, measurement, noise level in data, etc. For the synthetic data to be useful in real-world applications, there must be a *domain shift* or *domain transformation* to the synthetic data that, in theory, produces experimental results that are very similar to real field data. This is a growing research field of research. In the first year, we have primarily worked with two software packages – CARLA and IPG CarMaker, inside the scope of this project to perform high-fidelity simulations. The dSPACE Automotive Simulation Models (ASM) software is also being researched using resources from EcoCar and the ORNL National

Transportation Research Center (NTRC) partners. Sample data from each simulation package is shown in Figure 7 along with a specific example of an AV crash data visualization.

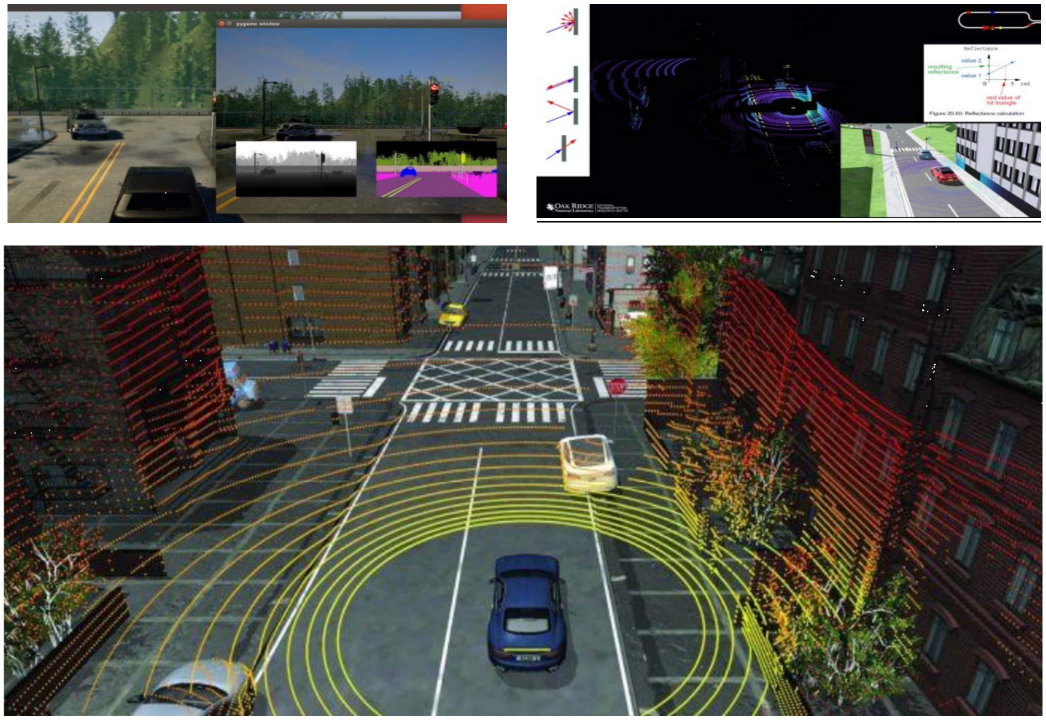

Figure 7: Synthetic data generated in CARLA (top left), IPG CarMaker (top right) and dSPACE ASM (bottom).

Data Visualization

As shown in the data collected from CARLA simulation #1, it can be seen that multiple camera angles, as well as what amounts to a 360° representation from LiDAR, are available for analysis with a minimal amount of technical post-processing. Figure 8 shows a simple visualization of the data that can be obtained directly

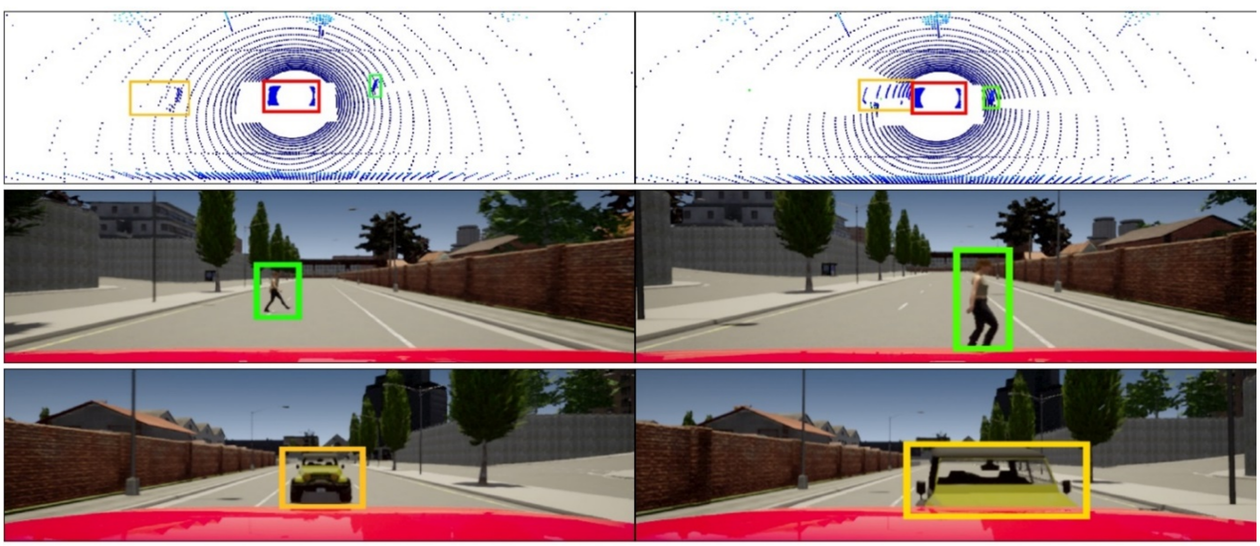

Figure 8. Visualization of CARLA sensors. LiDAR and Radar (Top), front-facing camera (middle), rear-facing camera (bottom), 1.14 seconds before collision(left), at vehicle impact(right). Pedestrian (green), following vehicle (orange), and AV (red) are color coded for all sensor modalities.

from an AV following a crash. This data is synchronized across all modalities, and in this case, shows all data obtained from the vehicle in the moments prior to rapid deceleration of the AV due to proximity to a pedestrian, as well as the moment after collision. Visualization such as what is shown in Figure 8 can be done easily and rapidly. Making this data available to researchers could allow a rapid and accurate understanding of what took place, how the sensors performed and the failure points in hardware and software.

Sensor degradation and counterfactual comparison

As we have shown, simulation can be a tool for event construction and a way to visualize sensor data. However, one of the primary benefits of AV simulation is the ability to control many different independent variables and insert or retract details into the simulation. To illustrate this, a second simulation was performed. In Figure 9, we show the results from Carla Simulation #2. In this approach, a scenario with a known AV and human response can be modified to test a potentially dangerous scenario in a simulated environment. Counterfactual simulations of known accidents such as is demonstrated in Figure 9 could be a potential avenue for a deeper understanding of AV responses in adverse situations. For example, the LiDAR data that is partially corrupted by a 40% drop out rate could return vastly different results when applied to a 3D object detection algorithm. The software tools needed for this performance testing is being developed. The effect of rain on lane detection is also demonstrated in Figure 10.

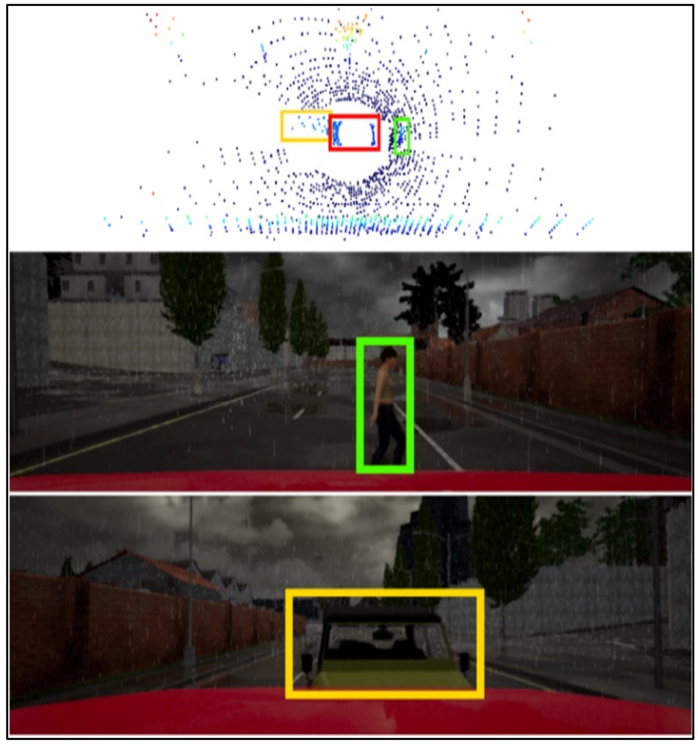

Figure 9 CARLA Simulation #2 is shown. All sensor data is shown to be degraded by rain. Pedestrian (green), following vehicle (orange), and AV (red) are color coded for all sensor modalities.

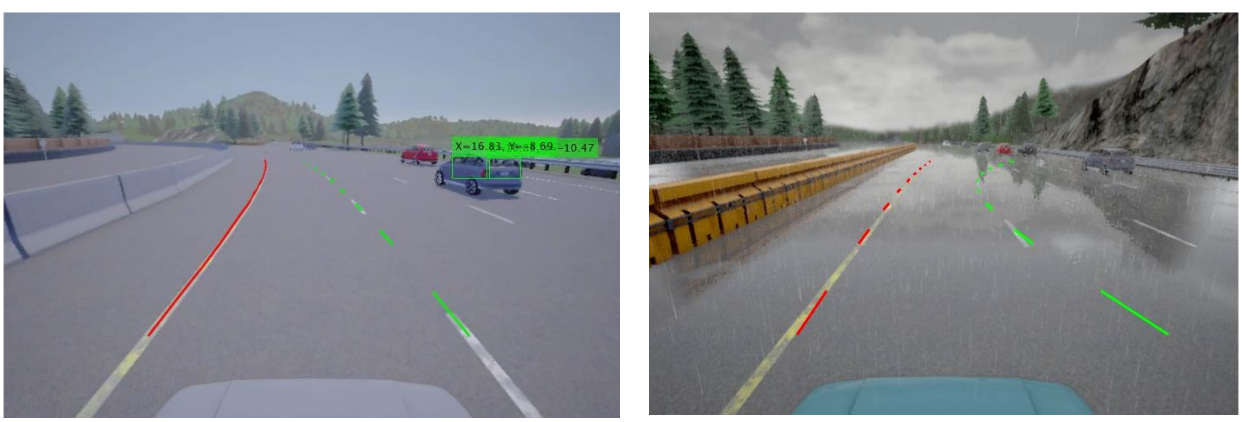

Figure 10. Demonstration of the failure of lane following in heavy rain with poor visibility of lane markings

Additional efforts were initiated on using simulations with real AV data (Arvin et al., 2020). Specifically, SUMO simulations were conducted to evaluate safety performance of Avs in mixed traffic with conventional vehicles at conflicts points, i.e., traffic intersections. The study uses SUMO (and associated software VENTOS) to model the following behavior of Avs. The study uses the Adaptive Cruise Control (ACC) and Cooperative Adaptive Cruise Control (CACC) models developed and calibrated by the California PATH team, University of California at Berkeley. Conventional vehicles are modeled using the Wiedemann model and calibrated with Michigan CV data. The results revealed that in at low levels of ACC market penetration, the safety improvement was not substantial, while with 40% ACC market penetration, safety improved substantially. Furthermore, by adding the cooperation dimension in terms of CACC at lower levels of market penetration, additional safety improvements can be achieved compared with ACC.

5.2. Missing data generation:

There are data streams and data features available in real sensors that are not available in virtual sensors, and vice-versa. There is a research opportunity to bridge the gap in missing data generation aspects through various techniques. One such example is our current research into efficiently reproducing the lidar intensity channel in synthetic data using a Convolutional Neural Network and sensor fusion techniques, as shown in Figure 11. Specifically, a Convolutional Neural Network (CNN) was trained to reproduce the lidar intensity channel successfully through sensor fusion with an RGB (Red, Green, Blue) camera. An image from the KITTI dataset is used as input to the CNN, which provides a reasonable prediction of objects in the image.

5.3. Data Validation:

Similar to the problem of domain shift (i.e., change in distribution of data from the training dataset, to when the algorithm is deployed in the field), it is difficult to interpret important characteristics of both synthetic and real data, and in turn rank order them by importance. The full pipeline from synthetic data generation to actual vehicle response provides a research opportunity to quantitatively validate data based on actual vehicle response. Our partnership with Duke University is addressing the gathering of such data.

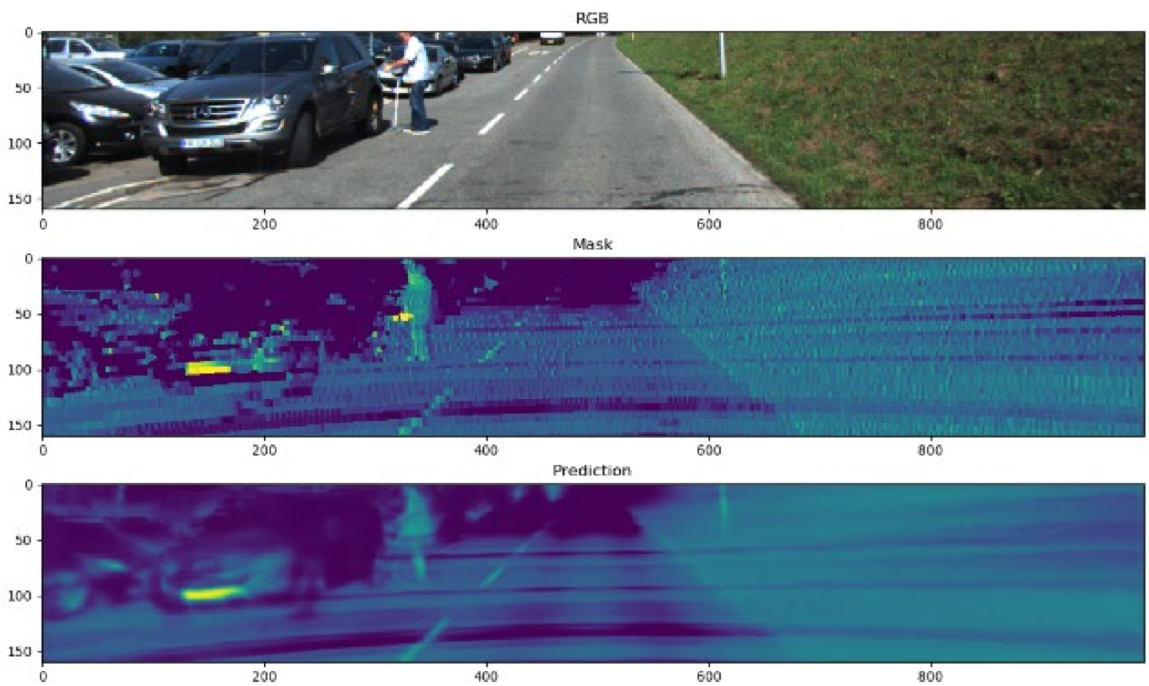

Figure 11: Convolutional Neural Network (CNN) trained to reproduce the lidar intensity channel through sensor fusion with an RGB camera. (TOP): RGB image from the KITTI dataset used as input to the neural net. (MIDDLE): Interpolated mask generated from real lidar data. (BOTTOM): Lidar intensity map prediction from the neural net.

5.4. Techniques for real-time execution:

It is important to note that synthetic data generation is secondary to our primary goal of realistic vehicle simulation. With that in mind, we explore novel ways of efficiently producing data in real time, such that realistic vehicle response is possible and simulated.

6. Automated Vehicle Hardware-in-the-loop (HIL) Simulation

Hardware-in-the-Loop (HIL) simulation is needed to capture the aspects of the vehicle that cannot be easily modelled in simulation. These include on board controllers, controller communication, vehicle HMI, and vehicle dynamics. To account for this, the UTK team has been granted access to a state-of-the-art Oak Ridge National Laboratory's NTRC facility where a vehicle was fitted to a steerable dynamometer for the express purpose of HIL simulation. Current goals related to this task are discussed below.

Figure 12: The RotoTest simulator featuring vehicle mounted on a steerable dyno with virtual sensors has been commissioned and it is ready for testing. (Source: Shean Huff, Oak Ridge National Laboratory)

6.1. Operation of ORNL NTRC Rototest Simulator

A Software-In-the-Loop (SIL) simulation must model and simulate vehicle hardware as well as intrinsic and extrinsic vehicle dynamics. By using this state-of-the-art steerable chassis dynamometer now available at the ORNL NTRC facility, we can improve realism of the experiment by supplying an actual vehicle with simulated input while it is operating in a controlled environment. This will produce a more realistic result with a hardware-in-the-loop (HIL) approach. In year 1, the simulator was commissioned and it is now operational.

6.2. Hardware-In-the-Loop Integration

The objectives of this project will be achieved by running simulations with real vehicle hardware. We currently have access to dynamometers, lidar sensors, radar sensors, various cameras, and sensor processing specific hardware. This allows research to be tailored to real situations encountered in AV testing, and not just purely running software-based simulation.

6.3. Comma Two system

Vehicle control is the cornerstone to research being done on testing AV's. The Comma Two system, which is commercially available, will allow us full access to the information available in our vehicle hardware, as well as control over all driver assistance features. In conjunction with the inherently safe Rototest Simulator, this allows a full bevy of control-based software to be implemented by our team without relying on OEM software that has no available source code.

7. Vehicle Response

Synthetic data generation and HIL simulation are ideally suited pathways to measure vehicle response in complex driving situations. If synthetic data can be used to test scenarios that may not be possible to safely test in the real world, and HIL simulation can be used to maintain accurate vehicle behavior, then there is a complete pipeline to use vehicle response as a metric to any number of independent variables. Current goals related to this task are discussed below.

7.1. Fringe Scenario Testing

A key objective of this project is to provide a meaningful study of situations in which AV systems can degrade in terms of performance or fail, and to measure AV performance in these fringe situations, e.g., torrential rain or pedestrian dart-out in front of an AV. To do this, the complete pipeline from synthetic data to vehicle response must be in place in order to make any definitive conclusion regarding vehicle performance in fringe scenarios.

7.2. Overall System Integration in the TENA (Test and Training Enabling Architecture) framework

For a complete pipeline to realistic vehicle response in different driving situations, the obvious avenue is to begin using vehicle response as a quantitative measure in front-end design choices. Sensor type and orientation, data augmentation, and software techniques are needed and they can all be judged based on vehicle performance instead of intermediate approximations such as IoU score in the case of object detection algorithms.

To enable the interoperability of vehicles, communication and infrastructure hardware built with different suites of sensors, networks, hardware, and software, we are modeling our software base on the TENA framework (shown in Figure 13). TENA is a Test and Training Enabling Architecture, developed under a joint interoperability initiative within the U.S. Department of Defense. The core of TENA is the TENA Common Infrastructure, including the TENA Middleware, the TENA Repository, and the TENA Object Models.

We are designing the TENA Middleware to be a high-performance, real-time, low-latency communication infrastructure that controls and interprets the exchange of data and control commands between TENA objects. The interpretation of vehicle CAN bus data (such as linear and lateral velocity, acceleration, steering angle, brake position, wheel torque, etc.) as well as BSM data will be performed by converting into a standard format acceptable by the virtual world models. Initial testing with a Toyota Rav 4 mounted on the Rototest steerable dyno has been performed by our ORNL NTRC collaborators, with real time data transfer between the vehicle and the simulator.

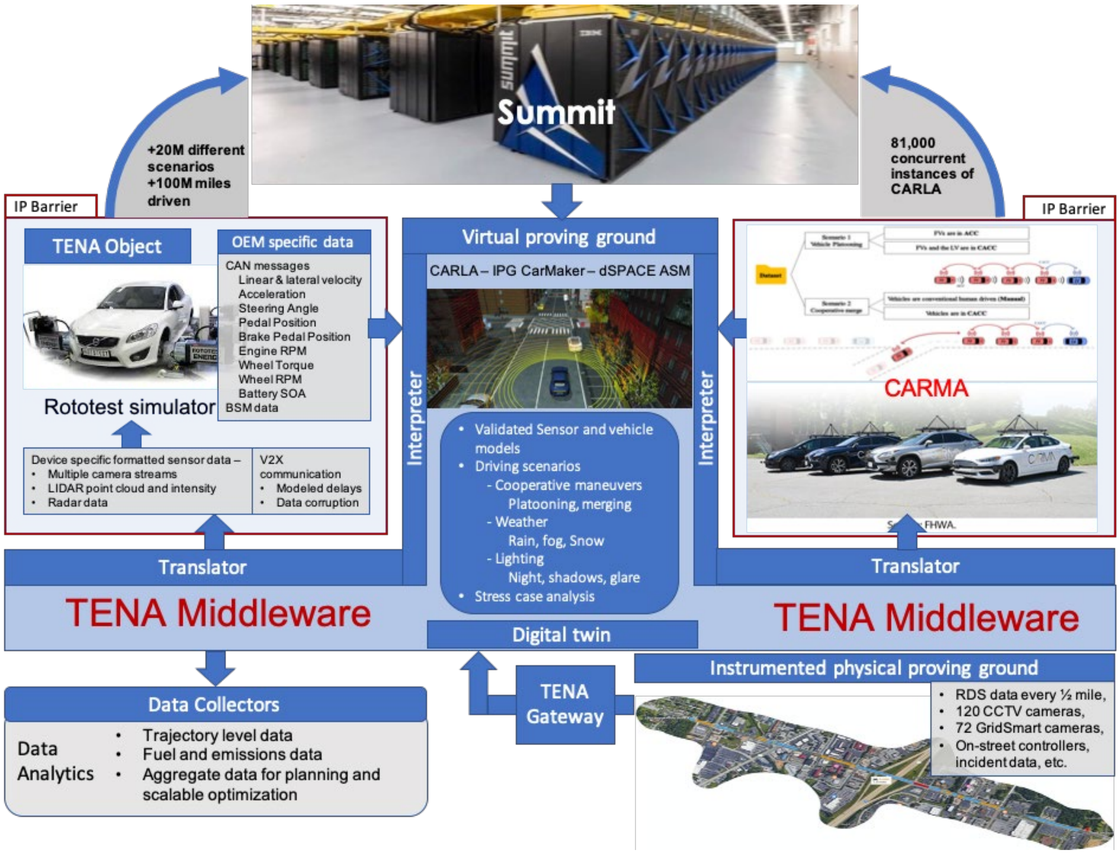

Figure 13: Three highlights of the TENA framework – Summit supercomputer application for concurrent testing with multiple CARLA instances, Rototest simulator with real vehicles in the loop, instrumented physical proving ground for V2I implementation and testing

The TENA Middleware is responsible for running the digital avatars of these vehicles, as well as translating the synthetic sensor data to resemble the format expected by the specific TENA object.

In Year 2, these efforts will continue in terms of developing an end-to-end solution of car-in-the-loop simulator with realistic sensor data generation from designed scenarios for stress testing vehicle AI. The table below outlines the high-level action items completed for each respective category in the past year.

Year 1 Completed Items		
ITEM	**Data Generation**	**HIL Simulation**
Research and document current state of the art in vehicle simulation.	☒	☒
Develop a convolutional neural network (CNN) that can allow the intensity channel found in real lidar data to be reproduced accurately in simulation.	☒	☐

Incorporate noiseless lidar, radar, and RGB camera image sensors inside a custom UE4 simulator.	☒	☐
Purchase and collect sample data from state-of-the-art lidar and radar sensors.	☐	☒
Produce simple data pipeline between CARLA and MatLab's Automated Driving Toolbox for rapid testing and development.	☒	☒
Understand impacts of AVs at conflict points using SUMO and AV testbed data from Ann Arbor, MI.	☒	☒
Set up development station for NVIDIA Drive PX2 for quick hardware implementation.	☐	☒
Begin using publicly available datasets provided to the Academic community by projects and companies as KITTI, Lyft, and Waymo as a method of exploring the features of state-of-the-art data.	☒	☐
Begin exploring techniques to synthetically produce lidar data, capturing situational noise.	☒	☐

8. Stakeholder Engagement

We have been in communication with the USDOT FHWA Turner-Fairbank Highway Research Center on simulating and testing CAVs and also engaged with Oak Ridge National Laboratory. We have engaged with United Laboratories (UL) staff as a private sector partner. We will work with our TennSMART partners that has a mix of public and private sector partners. For example, they include private sector stakeholders such as Bridgestone Americas, DENSO, FedEx, Fujitsu, GRIDSMART, Local Motors, Lyft, Miovision, Nissan North America, Soft Serve, Stantec Consulting Services, and 3M. Additionally, our international collaboration efforts on AV development, especially the identification of abnormal driving behaviors and application of analytic methods are reflected in journal publications (Jia et al., 2019); (Li et al., 2020).

9. Conclusion

Based on the work done in Year 1, the research team has documented the activities in this report. As a first step toward developing a framework for testing CAVs, ultimately leading to improved safety and specific recommendations. We are continuing to perform a comprehensive literature review and identify the gaps in current studies. Our activities have also focused on the integration of software and hardware platforms, and included scenario development, creating interfaces physical and virtual setups, such as hardware-in-the-loop testing. This is being done in collaboration with the Oak Ridge National Laboratory which has advanced testing facilities. Specifically, the test facility available at ORNL includes vehicle dynamometers where actual vehicles can operate at realistic speeds while being monitored (statically). Furthermore, we have initiated a structured testing protocol of driver monitoring and performance in various dimensions, e.g., that include roadway and environmental conditions (light conditions, weather conditions, visibility of lane markings), driver conditions (interactions with pedestrians, engagement in driving task), and vehicle dimensions (performance of various systems). We are particularly interested in conditions that can cause questionable system responses. Finally, industry and stakeholder engagement has been initiated.

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Appendix:

Safety Test Scenarios for AVs (1/6): Fringe Cases marked with *

Day / Night * Clear / Rainy * / Snowy * / Foggy *		**An AV drives alone.**	**An AV follows a conventional vehicle.**
Local Roads	**Straight Segments**	Driving forward	Driving forward
		Changing lanes	Changing lanes
		-	Overtaking the leading car
		Backing up	-
		-	Stopping behind the leading car
		Stopping for emergency	Stopping for emergency
		Vehicle merging from the roadside *	Vehicle merging from the roadside *
		Animal crossing *	Animal crossing *
		Pedestrian crossing *	Pedestrian crossing *
		Cyclist crossing *	Cyclist crossing *
		Road debris *	Road debris *
		-	Sudden stop of the leading car *
	Curved Segments	Driving forward	Driving forward
		Changing lanes	Changing lanes
		-	Overtaking the leading car
		-	Stopping behind the leading car
		Stopping for emergency	Stopping for emergency
		Vehicle merging from the roadside *	Vehicle merging from the roadside *
		Animal crossing *	Animal crossing *
		Pedestrian crossing *	Pedestrian crossing *
		Cyclist crossing *	Cyclist crossing *
		Road debris *	Road debris *
		-	Sudden stop of the leading car *
	Intersection	Driving forward	Driving forward
		Left turn	Left turn
		Right turn	Right turn
		Stopping for sign/signal	Stopping for sign/signal
		Stopping for emergency	Stopping for emergency
		Vehicle merging from the roadside *	Vehicle merging from the roadside *
		Animal crossing *	Animal crossing *
		Pedestrian crossing *	Pedestrian crossing *
		Cyclist crossing *	Cyclist crossing *
		Road debris *	Road debris *
		-	Sudden stop of the leading car *

Safety Test Scenarios for AVs (2/6): Fringe Cases with *

Day / Night * Clear / Rainy * / Snowy * / Foggy *		**An AV is followed by a conventional vehicle.**	**An AV follows another AV.**
Local Roads	**Straight Segments**	Driving forward	Driving forward
		Changing lanes	Changing lanes
		Overtaken by the following car	Overtaking the leading car
		-	-
		-	Stopping behind the leading car
		Stopping for emergency	Stopping for emergency
		Vehicle merging from the roadside *	Vehicle merging from the roadside *
		Animal crossing *	Animal crossing *
		Pedestrian crossing *	Pedestrian crossing *
		Cyclist crossing *	Cyclist crossing *
		Road debris *	Road debris *
		-	Sudden stop of the leading car *
	Curved Segments	Driving forward	Driving forward
		Changing lanes	Changing lanes
		Overtaken by the following car	Overtaking the leading car
		-	Stopping behind the leading car
		Stopping for emergency	Stopping for emergency
		Vehicle merging from the roadside *	Vehicle merging from the roadside *
		Animal crossing *	Animal crossing *
		Pedestrian crossing *	Pedestrian crossing *
		Cyclist crossing *	Cyclist crossing *
		Road debris *	Road debris *
		-	Sudden stop of the leading car *
	Intersection	Driving forward	Driving forward
		Left turn	Left turn
		Right turn	Right turn
		Stopping for sign/signal	Stopping for sign/signal
		Stopping for emergency	Stopping for emergency
		Vehicle merging from the roadside *	Vehicle merging from the roadside *
		Animal crossing *	Animal crossing *
		Pedestrian crossing *	Pedestrian crossing *
		Cyclist crossing *	Cyclist crossing *
		Road debris *	Road debris *
		-	Sudden stop of the leading car *

Safety Test Scenarios for AVs (3/6): Fringe Cases with *

Day / Night * Clear / Rainy * / Snowy * / Foggy *		An AV is followed by another AV.	An AV drives in traffic stream. (Penetration Rate: 0, 25, 50, 75, 100%)
Local Roads	Straight Segments	Driving forward	Driving forward
		Changing lanes	Changing lanes
		Overtaken by the following car	Overtaking the leading car
		-	-
		-	Stopping behind the leading car
		Stopping for emergency	Stopping for emergency
		Vehicle merging from the roadside *	Vehicle merging from the roadside *
		Animal crossing *	Animal crossing *
		Pedestrian crossing *	Pedestrian crossing *
		Cyclist crossing *	Cyclist crossing *
		Road debris *	Road debris *
		-	Sudden stop of the leading car *
	Curved Segments	Driving forward	Driving forward
		Changing lanes	Changing lanes
		Overtaken by the following car	Overtaking the leading car
		-	Stopping behind the leading car
		Stopping for emergency	Stopping for emergency
		Vehicle merging from the roadside *	Vehicle merging from the roadside *
		Animal crossing *	Animal crossing *
		Pedestrian crossing *	Pedestrian crossing *
		Cyclist crossing *	Cyclist crossing *
		Road debris *	Road debris *
		-	Sudden stop of the leading car *
	Intersection	Driving forward	Driving forward
		Left turn	Left turn
		Right turn	Right turn
		Stopping for sign/signal	Stopping for sign/signal
		Stopping for emergency	Stopping for emergency
		Vehicle merging from the roadside *	Vehicle merging from the roadside *
		Animal crossing *	Animal crossing *
		Pedestrian crossing *	Pedestrian crossing *
		Cyclist crossing *	Cyclist crossing *
		Road debris *	Road debris *
		-	Sudden stop of the leading car *

Safety Test Scenarios for AVs (4/6): Fringe Cases with *

Day / Night * Clear / Rainy * / Snowy * / Foggy *		An AV drives alone	An AV follows a conventional vehicle.
Highways (Arterials)	Straight Segments	Driving forward	Driving forward
		Changing lanes	Changing lanes
		-	Overtaking the leading car
		Backing up	-
		-	Stopping behind the leading car
		Stopping for emergency	Stopping for emergency
		Animal crossing *	Animal crossing *
		Road debris *	Road debris *
		-	Sudden stop of the leading car *
	Curved Segments	Driving forward	Driving forward
		Changing lanes	Changing lanes
		-	Overtaking the leading car
		-	Stopping behind the leading car
		Stopping for emergency	Stopping for emergency
		Animal crossing *	Animal crossing *
		Road debris *	Road debris *
		-	Sudden stop of the leading car *
	Intersection	Driving forward	Driving forward
		Left turn	Left turn
		Right turn	Right turn
		Stopping for sign/signal	Stopping for sign/signal
		Stopping for emergency	Stopping for emergency
		Animal crossing *	Animal crossing *
		Pedestrian crossing *	Pedestrian crossing *
		Cyclist crossing *	Cyclist crossing *
		Road debris *	Road debris *
		-	Sudden stop of the leading car *
Freeway or Interstate	Straight Segments	Driving forward	Driving forward
		Changing lanes	Changing lanes
		-	Overtaking the leading car
		Backing up	-
		-	Stopping behind the leading car
		Stopping for emergency	Stopping for emergency
		Animal crossing *	Animal crossing *
		Road debris *	Road debris *
		-	Sudden stop of the leading car *
	Curved Segments	Driving forward	Driving forward
		Changing lanes	Changing lanes
		-	Overtaking the leading car
		-	Stopping behind the leading car
		Stopping for emergency	Stopping for emergency
		Animal crossing *	Animal crossing *
		Road debris *	Road debris *
		-	Sudden stop of the leading car *
	Ramp	Entering the Freeway/Interstate	Entering the Freeway/Interstate
		Exiting the Freeway/Interstate	Exiting the Freeway/Interstate
		-	Stopping behind the leading car
		Stopping for emergency	Stopping for emergency
		Road debris *	Road debris *
		-	Sudden stop of the leading car *
	Directional Interchange	Driving forward	Driving forward
		Entering the ramp	Entering the ramp
		Left turn	Left turn
		Right turn	Right turn
		Entering another Freeway/Interstate	Entering another Freeway/Interstate
		-	Stopping behind the leading car
		Stopping for emergency	Stopping for emergency

		Road debris *	Road debris *
		-	Sudden stop of the leading car *

Safety Test Scenarios for AVs (5/6): Fringe Cases with *

Day / Night * Clear / Rainy * / Snowy * / Foggy *		**An AV is followed by a conventional vehicle.**	**An AV follows another AV.**
Highways (Arterials)	**Straight Segments**	Driving forward	Driving forward
		Changing lanes	Changing lanes
		Overtaken by the following car	Overtaking the leading car
		-	-
		-	Stopping behind the leading car
		Stopping for emergency	Stopping for emergency
		Animal crossing *	Animal crossing *
		Road debris *	Road debris *
		-	Sudden stop of the leading car *
	Curved Segments	Driving forward	Driving forward
		Changing lanes	Changing lanes
		Overtaken by the following car	Overtaking the leading car
		-	Stopping behind the leading car
		Stopping for emergency	Stopping for emergency
		Animal crossing *	Animal crossing *
		Road debris *	Road debris *
		-	Sudden stop of the leading car *
	Intersection	Driving forward	Driving forward
		Left turn	Left turn
		Right turn	Right turn
		Stopping for sign/signal	Stopping for sign/signal
		Stopping for emergency	Stopping for emergency
		Animal crossing *	Animal crossing *
		Pedestrian crossing *	Pedestrian crossing *
		Cyclist crossing *	Cyclist crossing *
		Road debris *	Road debris *
		-	Sudden stop of the leading car *
Freeway or Interstate	**Straight Segments**	Driving forward	Driving forward
		Changing lanes	Changing lanes
		Overtaken by the following car	Overtaking the leading car
		-	-
		-	Stopping behind the leading car
		Stopping for emergency	Stopping for emergency
		Animal crossing *	Animal crossing *
		Road debris *	Road debris *
		-	Sudden stop of the leading car *
	Curved Segments	Driving forward	Driving forward
		Changing lanes	Changing lanes
		Overtaken by the following car	Overtaking the leading car
		-	Stopping behind the leading car
		Stopping for emergency	Stopping for emergency
		Animal crossing *	Animal crossing *
		Road debris *	Road debris *
		-	Sudden stop of the leading car *
	Ramp	Entering the Freeway/Interstate	Entering the Freeway/Interstate
		Exiting the Freeway/Interstate	Exiting the Freeway/Interstate
		-	Stopping behind the leading car
		Stopping for emergency	Stopping for emergency
		Road debris *	Road debris *
		-	Sudden stop of the leading car *
	Directional Interchange	Driving forward	Driving forward
		Entering the ramp	Entering the ramp
		Left turn	Left turn
		Right turn	Right turn
		Entering another Freeway/Interstate	Entering another Freeway/Interstate

		-	Stopping behind the leading car
		Stopping for emergency	Stopping for emergency
		Road debris *	Road debris *
		-	Sudden stop of the leading car *

Safety Test Scenarios for AVs (6/6): Fringe Cases with *

Day / Night * Clear / Rainy * / Snowy * / Foggy *		**An AV is followed by another AV.**	**An AV drives in traffic stream. (Penetration Rate: 0, 25, 50, 75, 100%)**
Highways (Arterials)	**Straight Segments**	Driving forward	Driving forward
		Changing lanes	Changing lanes
		Overtaken by the following car	Overtaking the leading car
		-	-
		-	Stopping behind the leading car
		Stopping for emergency	Stopping for emergency
		Animal crossing *	Animal crossing *
		Road debris *	Road debris *
		-	Sudden stop of the leading car *
	Curved Segments	Driving forward	Driving forward
		Changing lanes	Changing lanes
		Overtaken by the following car	Overtaking the leading car
		-	Stopping behind the leading car
		Stopping for emergency	Stopping for emergency
		Animal crossing *	Animal crossing *
		Road debris *	Road debris *
		-	Sudden stop of the leading car *
	Intersection	Driving forward	Driving forward
		Left turn	Left turn
		Right turn	Right turn
		Stopping for sign/signal	Stopping for sign/signal
		Stopping for emergency	Stopping for emergency
		Animal crossing *	Animal crossing *
		Pedestrian crossing *	Pedestrian crossing *
		Cyclist crossing *	Cyclist crossing *
		Road debris *	Road debris *
		-	Sudden stop of the leading car *
Freeway or Interstate	**Straight Segments**	Driving forward	Driving forward
		Changing lanes	Changing lanes
		Overtaken by the following car	Overtaking the leading car
		-	-
		-	Stopping behind the leading car
		Stopping for emergency	Stopping for emergency
		Animal crossing *	Animal crossing *
		Road debris *	Road debris *
		-	Sudden stop of the leading car *
	Curved Segments	Driving forward	Driving forward
		Changing lanes	Changing lanes
		Overtaken by the following car	Overtaking the leading car
		-	Stopping behind the leading car
		Stopping for emergency	Stopping for emergency
		Animal crossing *	Animal crossing *
		Road debris *	Road debris *
		-	Sudden stop of the leading car *
	Ramp	Entering the Freeway/Interstate	Entering the Freeway/Interstate
		Exiting the Freeway/Interstate	Exiting the Freeway/Interstate
		-	Stopping behind the leading car
		Stopping for emergency	Stopping for emergency
		Road debris *	Road debris *
		-	Sudden stop of the leading car *
	Directional Interchange	Driving forward	Driving forward
		Entering the ramp	Entering the ramp
		Left turn	Left turn

		Right turn	Right turn
		Entering another Freeway/Interstate	Entering another Freeway/Interstate
		-	Stopping behind the leading car
		Stopping for emergency	Stopping for emergency
		Road debris *	Road debris *
		-	Sudden stop of the leading car *

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