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FINAL REPORT

Advancing crash investigation with connected and automated vehicle data – Phase 2

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1. Clark, K., Clamann, M., & Khattak, A. (2021). Advancing crash investigation with connected and automated vehicle data. Transportation Research Board, 100th Annual Meeting, Washington, DC. [Note: This paper reflects work in Phase 1 of this project.]
2. Beck, J., Arvin, R., Lee, S., Khattak, A., & Chakraborty, S. (2023, February). Automated vehicle data pipeline for accident reconstruction: New insights from LiDAR, camera, and radar data. Accident Analysis and Prevention, 180, 106923. https://doi.org/10.1016/j.aap.2022.106923
3. Lee, S., Arvin, R., & Khattak, A. J. (2023). Advancing investigation of automated vehicle crashes using text analytics of crash narratives and Bayesian analysis. Accident Analysis and Prevention, 181, 106932. https://doi.org/10.1016/j.aap.2022.106932
4. King, M., Khattak, A., Adeel, M., & Usman, S. (2024). Advancing crash investigation with connected and automated vehicle data: Insights from a survey of law enforcement. TRBAM-24-02430. Transportation Research Board 103rd Annual Meeting, Washington, DC.

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16. Abstract

This report explores the advancement of crash investigation through connected and automated vehicle data by answering several research questions: (1) What insights can be gained from automated vehicle (AV) crashes? (2) What are the gaps in AV safety performance? (3) Which crash contributors are revealed by AV sensors? (4) What pertinent information is missing in crash investigations? (5) What is the preparedness of law enforcement to use AV data? And (6) What insights are gained from on-road AV crash narratives? The results revealed that AV sensors provide valuable information about vehicle trajectories, which is usually unavailable. The above questions (2 and 6) are addressed by combining text analytics of crash narratives and Bayesian methods to assess how pre-crash conditions, automated driving mode, and crash types are associated with crash severity. This method revealed that AVs operating on ramps or slip lanes often experience higher injury severity. Questions 4 and 5 are addressed by surveying crash investigators in law enforcement and assessing their familiarity and experience with AV data. The survey revealed a need for standardization in AV data retrieval and training processes, resulting in a list of pertinent training curricula for law enforcement. This report also motivates a discussion on proper training of crash investigators. It shows that data uncovered through AV sensors can enrich crash investigation practices by facilitating a comprehensive portrayal of crash events.

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1. Executive Summary

Overview

With the diffusion of connected and automated vehicle technology, transportation systems are rapidly advancing, and crash investigators must keep up with this technical revolution. Current crash investigation practices heavily rely on event data recorder (EDR) data, which provides information such as the vehicle's condition and operation leading to a crash. However, the currently available dataset lacks key information such as vehicle trajectory and roadway, surrounding vehicle, and driver factors. Fortunately, automated vehicles (AVs) contain sensors (e.g., radar, LiDAR, and others) and cameras that can provide law enforcement with a wealth of new information that can paint a clearer picture of the events leading up to a crash.

This project aims to investigate how connected and automated vehicle data can be used to advance crash investigation. The project addresses several research questions, including what insights can be gained from AV sensors, what pertinent information is lacking in crash investigations, and how law enforcement can better utilize AV data. The project takes a multipronged approach, with each chapter focusing on a special effort to address the research questions. Chapter 2 proposes a data pipeline that can process raw data from AV sensors into visible results for analysis by crash investigators. Chapter 3 creates a comprehensive dataset from crash records and applies path analysis and Bayesian analysis to assess how pre-crash conditions and AV driving mode affect the severity of a crash. Chapter 4 addresses the need for law enforcement training with AV data. Overall, this project aims to provide insights into how AV data can enhance crash investigation and improve road safety.

Research questions

This project addresses several research questions to determine how connected and automated vehicle data can be harnessed to advance crash investigations:

1. What do AVs tell us when they crash on the road?
2. What are the gaps in AV safety performance?
3. What insights about crash contributors can we uncover from AV sensors?
4. What pertinent information is lacking in crash investigations?
5. How can law enforcement be prepared to use AV data in crash investigations?
6. What insights can narratives of on-road AVs provide?

Multipronged approach

This report addresses the research questions in several distinct efforts, each listed under its chapter heading.

Chapter 2, Automated vehicle data pipeline for accident reconstruction: New insights from LiDAR camera and radar data, uses CARLA simulation software to understand better the safety implications of AVs. Knowing that AV sensors can uncover a tremendous amount of data during a crash, researchers propose a data pipeline that takes raw data from AV sensors and processes it into results that crash investigators can analyze. The results show that crash investigation can be greatly enhanced by incorporating AV sensors and perception system data.

Chapter 3, Advancing investigation of automated vehicle crashes using text analytics of crash narratives and Bayesian analysis, creates a comprehensive dataset from crash records, crash narratives, and spatial information and employs path analysis to assess how pre-crash conditions, AV driving mode, and crash types affect the injury and property damage severity of a crash. The Bayesian approach is applied to incorporate prior knowledge and inform sound inferences while dealing with small sample size. The study uncovered several key insights about AV crash behavior. AVs operating on a ramp or slip lane tend to be exposed to a higher risk of occupant injury (37.7%). This study has important implications for roadway design and crash mitigation with the advent of high-level vehicle automation.

Chapter 4, Phase II Survey for Law Enforcement: Advancing Crash Investigation with Connected and Automated Vehicle Data, builds on the efforts of the Phase I survey, which assessed current crash investigation practices using EDRs. This survey addresses the growing need for law enforcement training with AV data by asking law enforcement questions about the current training curriculum and their familiarity with topics such as AVs and advanced driver assistance systems (ADAS). The full questionnaire is provided in the appendix of this report. The results of the survey allowed the researchers to create a list of training topics that can be used by law enforcement and crash investigators to develop training curricula for AV topics.

Research Outputs

Publications and Presentations

1. Clark, K., Clamann, M., & Khattak, A. (2021). Advancing crash investigation with connected and automated vehicle data. Transportation Research Board 100th Annual Meeting, Washington, DC.
2. Beck, J., Arvin, R., Lee, S., Khattak, A., & Chakraborty, S. (2023). Automated vehicle data pipeline for accident reconstruction: New insights from LiDAR, camera, and radar data. Accident Analysis and Prevention, 180, 106923. https://doi.org/10.1016/j.aap.2022.106923
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4. King, M., Khattak, A., Adeel, M., & Usman, S. (2024). Advancing crash investigation with connected and automated vehicle data: Insights from a survey of law enforcement. TRBAM-24-02430. Transportation Research Board Annual 103rd Meeting, Washington, DC.

2. Automated Vehicle Data Pipeline for Accident Reconstruction: New Insights From LiDAR, Camera, and Radar Data

Introduction

The paper "Automated vehicle data pipeline for accident reconstruction: New insights from LiDAR, camera, and radar data" provides a framework for harnessing automated vehicle (AV) sensor data to extract useful information that can be incorporated into accident reconstruction analyses. The data is sourced from the California Autonomous Vehicle Tester Program; AV crashes are carefully selected after analyzing AV-crash statistics to find cases that are representative of a large proportion of AV crashes. A review of the current literature on crash investigations reveals that event data recorders (EDRs) are one of the most important and widely used data sources (Scanlon et al., 2015; Kusano & Gabler, 2013; Augenstein et al., 2007; Kononen et al., 2011), but EDRs are limited in that they only collect data from the subject vehicle and do not account for advanced driver assistance systems (ADAS) (Zhu & Meng, 2022; Wang & Li, 2019). With the emergence of AVs and more vehicles equipped with ADAS, there is a growing need to investigate crashes specific to AVs and how sensor data can supplement crash analyses (National Transportation Safety Board, 2017). The paper identifies and addresses a gap in the research regarding a framework for integrating AV sensor data (LiDAR, camera, and radar) into crash investigations.

Methods

The first part of this study is an analysis of existing California AV crash data. Of 94 crash cases where AVs were operating automatedly, around 70% were rear-end collisions. A significant portion (7.5%) of these cases involved pedestrians or bicyclists. From these statistical findings, two sample crash scenarios were developed: (1) an interaction between a pedestrian and an AV and (2) a rear-end conflict between AVs and conventional vehicles.

The next part of the study dealt with data processing to prepare for the simulation of the two crash scenarios in CARLA software. The Safe System framework is used, which incorporates data related to AV systems; the roadway environment; weather conditions; and the driver before, during, and after the crash. The study focuses on three data types: LiDAR 3D point cloud data, video from all available cameras, and position and velocity data supplied from inertial measurement units (IMUs) inside the vehicle. The raw data from AV sensors and conventional vehicle sensors (IMU, EDR, GPS) was organized and preprocessed to create outputs such as AV dynamics, involved vehicle dynamics, and pedestrian location. The Kitti dataset was used to validate the data processing procedure using the You Only Look Once (YOLO) image processing model.

After data is processed and simulation feasibility is demonstrated, the crash scenarios are ready to be simulated in CARLA. Because real-world data from AV accidents is sparse, a simulation tool such as CARLA can be used to produce data instead. CARLA uses a robust lanekeeping, car-following, and emergency-stopping algorithm for vehicle dynamics. Pre-programmed destination waypoints are used in this study to control for vehicle dynamics to ensure reliability.

The three AV data sources replicated in CARLA are camera, radar, and LiDAR. LiDAR within CARLA is produced using a tool called "ray-trace," which returns the location of any object encountered in a straight line in the simulated world. In this regard, simulated LiDAR operates under the same theory as real LiDAR but does not consider the physical properties of light, such as diffraction, dispersion, and reflection. Real-world radar tools use time-of-flight measurements of lower-frequency waves for object detection and are a cheaper solution than LiDAR. Simulated radar, however, functions similarly to simulated LiDAR in that ray tracing is used for object locations. Functions are applied to the data to more closely simulate radar, such as by applying noise, transforming the data to polar coordinates, and computing velocity. Similar to real cameras, simulated cameras provide RGB (red, green, blue). Simulated cameras require post-processing tools inside CARLA to achieve situational reconstruction images. Lastly, conventional sensors such as IMU, EDR, and GPS are used along with the AV sensors to provide position and velocity data.

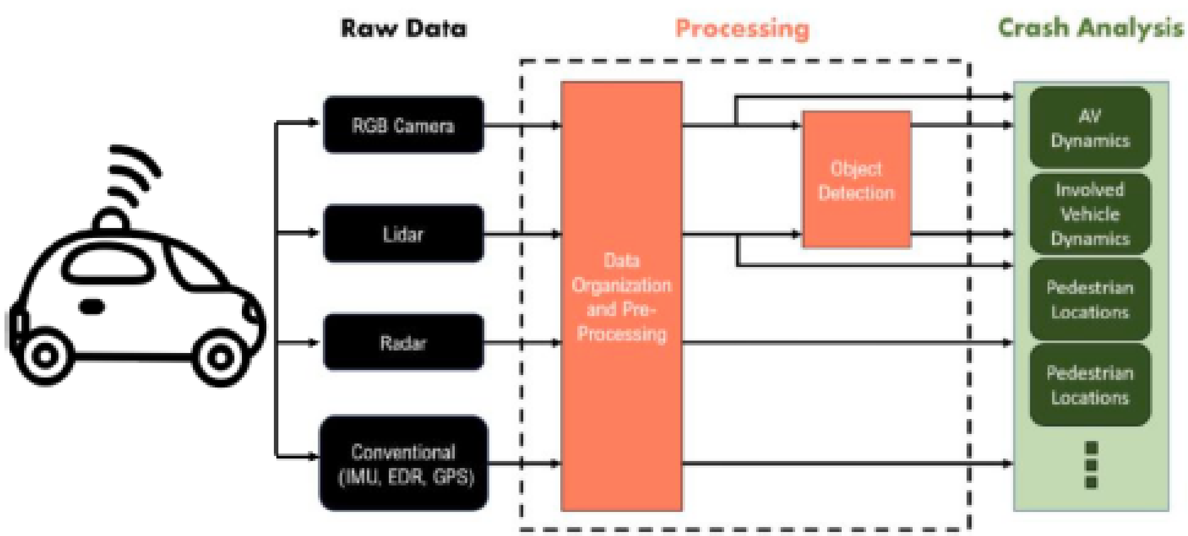

Figure 1: Proposed Data Pipeline

Findings

Insights into crash behavior can be gained by visualizing the output of the data pipeline as well as by applying further analyses. The immediate output of the CARLA simulation provides a 360-degree representation of LiDAR and radar data obtained from the vehicle before the rapid deceleration of the AV and the moment after a collision. Multiple conclusions could be made from this output, such as that the AV had the right of way during the sample scenario, and LiDAR could locate the incoming vehicle a second before the rear camera saw the vehicle. A deeper analysis provides vehicle trajectory, position, and velocity data typically unavailable in EDR data. From the analytical output, it could be determined that the conventional vehicle never applied its brakes since velocity never decreased. AV sensor data can provide this information and benefit crash investigators during accident reconstruction.

The study is not without limitations. The authors present the caveat that simulation tools are simplified or idealized versions of crash events. It follows that simulations such as CARLA should be used as a supplement to real AV crash data and not a replacement.

Table 1: Overview of Data Input into the Pipeline for CARLA Simulations #1 and #2

Sensor	Data Type	Data Size	Range	Update Rate
Camera	Image	480x720 pixels	≈ 10 (detection)	60 Hz
Radar	3D Point Cloud (Position + Velocity)	≈ 300 points	20 m	50 Hz
LiDAR	3D Point Cloud (Position + Velocity)	≈ 30,000 points	50 m	50 Hz
GPS + IMU	Vehicle Position + Velocity	1 point	N/A	Greater than 60 Hz

Conclusion

This study used the Safe Systems approach to create a framework for applying AV databases during crash investigations. The use of different AV sensors is demonstrated using CARLA simulation software to model two hypothetical AV crash scenarios. The crash scenarios were determined after analyzing real-world AV crash statistics. Due to a high propensity of rear-end crashes, conventional vehicle interactions, and pedestrian actions, one situation was modeled as a rear-end crash between an AV and a Jeep after the AV stopped to accommodate a jaywalking pedestrian. A second situation displays a mid-speed collision between a conventional vehicle and the rear right side of an AV in the middle of an intersection. After modeling these two situations in CARLA, several conclusions regarding crash events could be drawn from the AV data outputs. Namely, vehicle trajectory information is provided by AV sensors but is typically not available in EDR data. This study demonstrates that AV sensors provide new details to crash investigators regarding the state of the driver, the movement of vehicles, and the trajectories of surrounding objects and people. Future research should harness basic safety message (BSM) data on vehicle kinematics to further investigate the benefits that AV technologies can provide during the crash investigation process.

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3. Advancing Investigation of Automated Vehicle Crashes Using Text Analytics of Crash Narratives and Bayesian Analysis

Introduction

The paper Advancing investigation of automated vehicle crashes using text analytics of crash narratives and Bayesian analysis demonstrates how automated vehicle (AV) data can be leveraged to improve knowledge of AV safety in mixed traffic. Until the market penetration of AVs reaches 100 percent, AVs will interact with conventional vehicles, and it is critical to understand the safety effects of mixed traffic conditions. This study addresses this issue by scrutinizing 260 AV collision reports released by the California Department of Motor Vehicles (DMV) to form a comprehensive dataset containing crash information extracted from the reports. The findings from this study can provide a more thorough understanding of AV crashes for public agencies and developers, and the key factors identified can be included in the testing of high-level automation, as well as the development of vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) technology.

The past literature shows efforts to assess AV safety performance. Generally, previous studies have analyzed the California DMV reports. Past findings show that rear-end collisions are the most frequent type of AV-involved crash, and injury severity tends to be lower for AV crashes than for human-driven crashes (Sivak & Schoettle, 2015; Favarò et al., 2017; Ashraf et al., 2021; Kutela et al., 2022; McCarthy, 2022). AVs also have a higher proportion of rear-end collisions than conventional vehicles (Petrović et al., 2020: Goodall, 2021). Beyond descriptions of crash behaviors, some studies have attempted to identify influential factors concerning AV crash types, injuries, or vehicle damage (Wang & Li, 2019; Xu et al., 2019; Boggs et al., 2019). Rear-end collisions are positively correlated with the automated driving mode, one-way roads, roads with high traffic, intersections, and situations where an AV is stopped (Ashraf et al., 2021; Kutela et al., 2022; Wang & Li, 2019; Boggs et al., 2019). Further, higher injury severity is associated with crashes occurring on highways (Wang & Li, 2019), and injury crashes tend to be positively related to roadside parking, intersections, arterial roads, and rear-end collisions (Boggs et al., 2019). The authors have found a few gaps in the literature. First, previous studies have focused on a specific crash type or outcome, providing only fragmentary insights (Ashraf et al., 2021; Kutela et al., 2022; Wang & Li, 2019; Boggs et al., 2019; Das et al., 2020). This gap is addressed by considering complex interrelationships among several factors. Second, previous studies rely on limited variables from crash records without extracting additional variables from crash narratives (Boggs et al., 2019; Kutela et al., 2022). The study addresses this limitation by using text mining to extract other variables. Furthermore, the Bayesian approach is used to combine prior knowledge with the new dataset.

Methods

The conceptual framework of this study consists of two main tasks: the organization of a comprehensive dataset (N=260) of AV-involved crashes and a statistical analysis with a path analytic framework. The crash variables are organized into four layers: pre-crash conditions, AV driving modes, crash types, and crash outcomes. Further, there are three AV driving mode categories:

1. Pre-crash automated to during-crash automated.
2. Pre-crash automated to during-crash conventional.
3. Pre-crash conventional to during-crash conventional.

The framework has three data sources: crash records, crash narratives, and spatial information. Within the crash records, the authors extracted the following variables: vehicle manufacturers, AV driving modes, vehicle movements, AV interaction with pedestrians or bicyclists, manner of collision, AV damage level, and injury of at least one person. Text mining was applied to extract the following variables from the crash narratives: involving yielding or waiting, involving transit, and involving manual disengagement. Lastly, using Google to investigate the locations of crashes as reported in the narratives, the authors extracted the following variables: land use, road classification, and road segment types. A multinomial logit model was estimated to describe how pre-crash conditions influence the AV driving mode. Binary logistic models were estimated for the remaining response variables with binary (yes or no) outcomes. The binary logistic regressions are estimated to explain how pre-crash conditions and AV driving modes affect the crash type and how injury odds are affected by pre-crash conditions, AV driving modes, and crash types.

Next, an ordered logit model is applied to estimate how pre-crash conditions, AV driving modes, and crash types associate with AV damage levels. Lastly, a Bayesian approach is used in addition to the frequentist approach to reduce bias from the sample by applying informative prior distributions from the literature. For variables without appropriate prior knowledge available, uninformative prior distributions were applied.

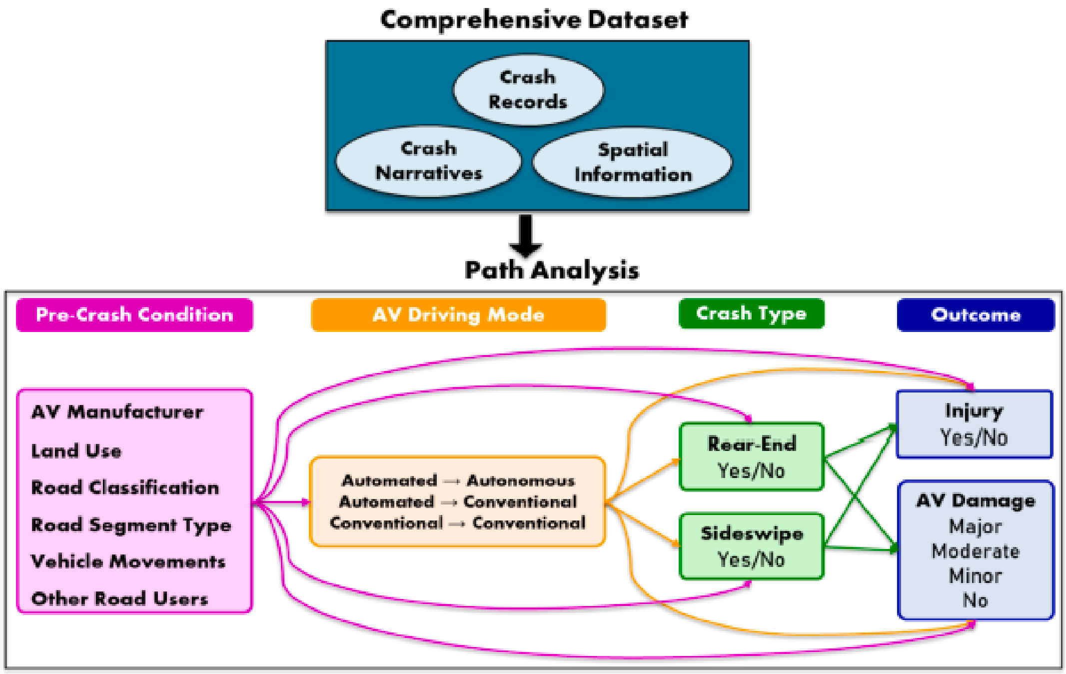

Figure 2: Conceptual Framework

Findings

Key descriptive statistics are summarized in Table 1. The frequentist and Bayesian analyses provided valuable insights along with the descriptive statistics. Regarding the AV driving mode, a multinomial logit model showed that AVs tend to be more vulnerable to rear-end collisions in the automated driving mode versus the conventional mode. Further, the AV driving mode did not significantly affect the chance of a sideswipe collision or crash outcomes. The binary logit models used to study crash types revealed no significant difference in the possibility of a rear-end collision when comparing manual disengagement and the conventional driving mode. The binary logit models used to estimate the relationships in crash outcomes revealed that the chance of injury crash has a negative association with manual disengagement, a positive relationship with intersections, and a positive relationship with infrastructure such as recreational areas, ramps, or slip lanes and interaction with pedestrians or bicyclists.

Table 2: Key Descriptive Statistics

Variable	Frequency	Percentage (%)
Vehicle Manufacturer		

Variable	Frequency	Percentage (%)
Cruise LLC	105	40.4
Waymo LLC	98	37.7
Other	57	21.9
AV Driving Mode		
Automated → Automated	104	40.0
Automated → Conventional (Manual Disengagement)	62	23.9
Conventional→ Conventional	94	36.2
Land Use		
Residential	102	39.2
Commercial	103	39.6
Recreational	11	4.2
Other	44	16.9
Road Classification		
Freeway/ Expressway / Highway	11	4.2
Street	222	85.4
Other	27	10.4
Road Segment Type		
Intersection	215	82.7
Ramp / Slip Lane	6	2.3
Other	39	15.0
Vehicle Movements (AV, Second Vehicle)		
(Stopped, Straight)	61	23.5
(Slowing/Stopping, Straight)	11	4.2
(Straight, Straight)	24	9.2
(Straight, Changing Lanes)	16	6.2
(Left, Straight)	10	3.9
Other	138	53.1
Involving an AV Yielding or Waiting	60	23.1

Variable	Frequency	Percentage (%)
Other Road Users		
Involving a Transit Vehicle	6	2.3
Involving a Pedestrian or Bicyclist	16	6.2
Crash Type		
Rear-End*	135	51.9
Sideswipe**	52	20.0
Other	73	28.1
Involving Injury to at Least One Person	50	19.2
AV Damage Level		
None	21	8.1
Minor	198	76.2
Moderate	38	14.6
Major	3	1.2

* 129 AVs (95.6 %) were rear-ended by another vehicle.

* *36 AVs (69.2 %) were sideswiped by another vehicle.

Conclusion

The results of this study have several key implications. AVs in the automated driving mode should deal with the longitudinal distance from the leading or following vehicles on the road to prevent rear-end collisions. This can be accomplished with improved detection and warning systems and better V2V communications. Critical infrastructure such as intersections, ramps, and slip lanes need to be designed to support AVs better, and AVs should undergo more thorough testing on these roadway features. The findings of this study can provide valuable insights to transportation planners and engineers into how to prepare for the future of mixed traffic conditions. While valuable insights were uncovered through this study, it has limitations. All of the crashes studied occurred within the state of California. Therefore, the results should not be generalized broadly across other regions. Some variables may be missing from the dataset, such as the exact vehicle trajectories or how vehicle speeds changed during a crash. Future research may need to distinguish AV crashes by whether the AV was striking or the AV was struck to develop further insights. It would also be useful to test the relationships identified in this study using future AV crash data to assess how AV technology is advancing.

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4. Survey for Law Enforcement: Advancing Crash Investigation with Connected and Automated Vehicle Data

Introduction

Understanding the contributing factors in more than 6 million vehicle crashes that occur annually in the United States is very challenging, and law enforcement officers investigating crashes need all the tools they can use to reconstruct the crash. Connected and automated vehicles (CAVs) mark the future of the transportation system, and the crashes involving these vehicles demand a greater focus on crash investigative practices to ensure accurate crash diagnosis and adoption of effective crash mitigation strategies. A total of 470 crashes involving CAVs with Level 2 automation (ADAS) occurred on U.S. national roads from October 2022 to July 2023. Notably, 2.5% of these crashes occurred in Tennessee (National Highway Traffic Safety Administration, 2023). Given that the CAV era is rapidly unfolding, this study seeks to leverage newly available CAV data to improve crash investigation procedures and obtain input from stakeholders, specifically law enforcement.

Currently, law enforcement relies on event data recorders (EDRs), which store vehicle kinematics—the fundamental aspects of vehicle movement, such as speed, lateral and longitudinal acceleration, position, and how they change over time in a crash. EDRs lack information such as vehicle trajectories, the behavior of surrounding vehicles and pedestrians, the behavior of the driver, and roadway conditions. Information gathered by Automated Driving System (ADS) technologies such as radar, cameras, LiDAR, infrared, and ultrasonic could help fill some data gaps in a crash investigation. This detailed data could improve the fidelity of future crash investigations, with potential new information such as driver/operator state, vehicle automation capabilities, location, objects and people in the immediate area, performance and diagnostic data, and environmental factors. Through a survey with law enforcement officials, this study contributes by further understanding how CAV data can be harnessed to advance a crash investigation. Further, the study explores law enforcement involvement in training for using and applying CAV data, and we assess their knowledge of automated vehicle (AV) technology data. This research aims to produce a list of training topics to inform the curation of curriculums for law enforcement training in CAV technology.

Literature Review

The current body of literature provides a variety of techniques and technologies that are used in crash reconstruction. To properly investigate a crash, factors such as local conditions, series and sequence of harmful events, contributing circumstances from roadway, driver, and vehicle actors, vehicle speed, vehicle information and condition, date and time, location, insurance information, commercial vehicle information, emergency medical service (EMS) information, and fixed objects must be considered (Clamann et al., 2021). Conventional accident reconstruction methods rely on EDRs to recreate and understand the pre-crash conditions that led to the accident (Clamann et al., 2021; Scanlon et al., 2021). EDRs typically store data beginning 5 seconds before the triggering event occurs (Clamann et al., 2021). Triggering events occur when data that is sent from the sensors to the EDRs indicate that an impact exceeds a certain threshold, such as the deployment of the seatbelt pre-tensioner or airbags or significant accelerations (Clamann et al., 2021). The National Highway Traffic Safety Administration (NHTSA) (2001) provides a top ten list of data elements stored in EDRs: acceleration and direction of force; crash location; number and location of occupants; seatbelt status; pre-crash data; rollover sensor; yaw rate; time of crash; braking, traction, and stability information; and air bag information.

Detailed vehicle sensor data can be very valuable when recreating a vehicular accident. However, EDRs do not provide audio or visual data, which can greatly enhance a crash investigation. Multiple studies cite the usefulness of dashboard cameras during accident reconstruction (Lee & Lee, 2022; Giovannini et al., 2021; Stanton et al., 2019). In a study conducted by Jaehyeong Lee and Youngnae Lee (2022), dashboard camera sound was shown to be useful when calculating vehicle speed, especially in circumstances where the vehicle's torque converter slip is not severe or when it is necessary to check for engine RPM changes (intentional accidents). Another study by Giovannani et al. showed that dashboard camera footage was pivotal in accurately reconstructing a pedestrian and tractor-trailer crash (2021). Before analyzing the camera footage, the crash appeared to be accidental. However, the footage showed that the pedestrian suddenly darted in front of the moving vehicle, revealing that the collision resulted from suicide (Giovannini et al., 2021). Another well-known example of dashboard camera footage used to reconstruct crash events is Arizona's automated Uber – pedestrian crash in 2018 (Stanton et al., 2019). The Uber was a Volvo vehicle operating at Level 2 autonomy, and it failed to prevent colliding with (and killing) a crossing pedestrian. Using dashboard camera footage along with other vehicular data, Stanton et al. (2019) employed the Accimap method to map out the numerous circumstances that contributed to the crash. There is a need for more research that investigates how AV camera sensor (not just after-market dashboard camera) footage can enhance crash reconstruction.

LiDAR sensors can help reconstruct crash events. LiDAR is a range-finding environmental sensor commonly used to model terrain, and it can also be used for adaptive cruise control, collision avoidance, and object recognition (Clamann et al., 2021). Yakar et al. (2020) showed how LiDAR could be used in collaboration with unmanned aerial vehicle (UAV) photogrammetry and FARO simulation software to recreate crash events. In Yakar et al.'s 2020 study, laser scanning successfully represented the facades of vehicles. However, it is noted that UAV photogrammetry is more accurate than LiDAR. LiDAR is used in AVs for obstacle detection (Clamann et al., 2021); Catapang and Ramos test LiDAR equipment to show that 1.36-meter-wide obstacles can be reliably detected at distances less than 10.82 meters. Reliable classification of obstacles, however, is only achieved at distances of less than 5.42 meters (Catapang & Ramos, 2016). There is a gap in the research regarding how AV LiDAR data can be harnessed after crash events for accident reconstruction.

In addition to LiDAR, radar also holds value for crash reconstruction. Several studies in the literature cite radar for use by AVs in pedestrian/obstacle detection (Broggi et al., 2004; Clamann et al., 2021; Zolock et al., 2016). Broggi et al. (2004) and Clamann et al. (2021) both note that radar is highly effective at detecting pedestrians even in the presence of a complex background. Zolock et al. (2016) conducted experiments involving both moving and stationary obstacles to test the ability of radar to reconstruct vehicular position and motion information. Zolock et al. (2016) revealed that radar could accurately track both moving and fixed objects, which can be used during crash reconstruction. There is a need in the literature, however, to evaluate the effectiveness of radar in crash reconstruction using moving hosts and targets (Zolock et al., 2016).

A data source unique to connected vehicles is basic safety messages (BSMs), which are exchanged between connected vehicles using onboard units (OBUs). Both Clamann et al. (2021) and Arvin et al. (2019) discuss how these messages can provide pertinent vehicle information. Arvin et al. (2019) used a BSM dataset to capture variations in vehicle control. By capturing these variations and finding meaningful relationships between control variations and crash data, the usefulness of BSM data in crash investigations becomes worth further investigation. Clamann et al. (2021) do not perform any tests using BSM data. However, their study discusses how OBUs and BSMs can be used to understand other drivers' behaviors (Clamann et al., 2021).

The literature cites several simulation software tools used during a crash investigation. Among these are LS-DYNA, which Chen et al. (2021) used to model plastic deformation post-crash, PyCRASH (Cormier et al., 2021), PC-Crash (Muggenthaler et al., 2013), and Faro (Yakar et al., 2020).

The literature generally reveals that AVs provide many potential sources for post-crash data, including LiDAR, radar, cameras, and OBUs. While EDRs and crash simulation software are frequently used by crash reconstructionists, AV data is not yet being harnessed in industry practices to reconstruct accidents. There is a significant gap in the research for testing this data and using it to reconstruct real or simulated crashes. A lower frequency of AV crashes relative to non-AV crashes may contribute to why this data is not actively used by crash investigators and law enforcement (i.e., because of the lower market penetration of AVs than conventional vehicles, there are fewer AV crashes on the roads for investigators to reconstruct). While researchers are still studying AV market penetration rates and deployment predictions, automobile manufacturers such as Tesla, Waymo, Ford, and General Motor Company, among others, are producing vehicles with increasing automatic capabilities. Moreover, most new cars on the market include Advanced Driver Assistance Systems (ADAS) such as adaptive cruise control, hands-on lane-centering steering, and hands-free steering. Thus, as vehicular networks become increasingly automated, crash investigators and law enforcement can benefit by updating crash reconstruction processes to include AV sensor data.

Another gap in the research is understanding how law enforcement and crash investigators should be trained to handle CAV data and recreate AV-involved crashes. This study addresses this gap by delivering two questionnaires: one geared toward law enforcement to develop a list of CAV training topics, and one for crash investigators to gain further insights into how CAV data can be harnessed for crash reconstruction.

Methods

The survey is conducted through the Qualtrics online survey platform. The study population is officials from city police departments, sheriff's offices, and the Tennessee Highway Patrol. The respondents are Tennessee officials who specifically work in vehicle crash investigations. This includes 61 officials from a database of 326 local police departments and 95 sheriff's offices. All respondents are over the age of 21.

The respondents were contacted through a third party, with assistance from Mr. William Campbell from the Tennessee Highway Safety Patrol Office. Mr. Campbell emailed a survey link to the Tennessee law enforcement officials in crash investigation, and then the survey responses were delivered directly to the researchers. All responses are anonymous, and the researchers collected no personally identifying information. The survey begins with a statement of informed consent, and if respondents choose to consent to fill out the survey, they are then allowed to proceed to a brief background section. After reading the background, the respondents answered 24 questions: 11 multiple-choice questions, 9 short-answer questions, and 4 Likert scale matrix questions. The full questionnaire is available in the appendix of this report. The survey included the following questions:

1. How many sworn officers work in your organization?
2. Does your organization have a separate division charged with investigating crashes?
3. What is your role in collision investigation?
4. How many fatal and/or prosecutable crashes have you worked on?
5. Has your organization provided the opportunity for training on the use of AV sensor data for crash reconstruction purposes?
6. Does your organization have access to the processing or managing of crash data from vehicles involved in a collision?
7. Have you ever used vehicle camera footage during a crash investigation? If so, how did this footage impact the process and outcome of the investigation?
8. Have you ever used in-vehicle LiDAR equipment during a crash investigation? If so, how did this in-vehicle LiDAR data impact the process and outcome of the investigation?
9. Have you ever used in-vehicle radar sensors during a crash investigation? If so, how did the use of in-vehicle radar impact the process and outcome of the investigation?
10. What software or other tools do you typically use during a crash investigation (e.g., analysis and simulation software, total stations, drone cameras, event data recorders)?
11. Have you ever used event data recorders (EDRs) for collision investigation?
12. What information have you typically received from the EDR automatically after a collision?
13. Have you completed any training for EDR data retrieval? If so, please specify which course(s) you have completed.
14. Have you completed any training for AV data retrieval? If so, please specify which course(s) you have completed.
15. Does the current process of collision investigation adequately fulfill each of the following aspects of collision investigation? Rank adequacy using the provided scale points.
16. Is there anything else that could be improved about the current process of collision investigation?

17. Thinking of the future of collision investigation, what information (not usually available today) would you most like to get from a vehicle automatically after a collision?
18. Of the available data sources in AVs mentioned, which would provide the most helpful information that is not currently available? (Select all that apply.)
19. What are some significant barriers based on your work experience for using AV sensor data in crash reconstruction? (Select all that apply.)
20. Based on your work experience, how can AV sensor data enhance crash investigation? (Select all that apply.)
21. Please rate your familiarity with the following AV technologies using the provided scale points.
22. Please rate your familiarity with the following advanced driver-assistance system technologies using the provided scale points.
23. Please rate your familiarity with the following law enforcement training topics using the provided scale points.
24. Do you have any final thoughts regarding crash investigation, AV or advanced driver-assistance system technology, or other related topics?

Results

The research team performed data analysis for the survey using Qualtrics. The results are reported in several sections below. Descriptive statistics are reported for the survey, supplemented by graphical representations and text mining.

Survey Respondents – Work Context

A set of questions in the survey were used to understand the organizations and work experiences of the respondents. Descriptive statistics are reported in Tables 3-5, with Table 3 reporting continuous variables, Table 4 reporting multiple-select questions, and Table 5 reporting multiple-choice questions. Multiple-select is distinct from multiple-choice as multiple-select allows respondents to select multiple responses, whereas multiple-choice requires the respondent to select only one response. Therefore, response percentages for each question in Table 4 will sum to a value greater than 100%, whereas percentages for each question in Table 5 will total exactly 100%.

The introductory questions relate to the respondents' roles, organizational structures, and work experiences. From Table 3, the organizations contained an average of 435.5 sworn officers, with a range of 1,460 spanning from 5 to 1,465 officers. Table 3 also shows that each respondent has worked on an average of 160 fatal and/or prosecutable crashes, ranging from 0 to 1,700 individual crashes. Another question asks respondents to select multiple occupational roles that apply to themselves (crash reconstructionist, traffic division, patrol, and other); Table 4 shows that 91.1% selected crash reconstructionist, 39.3% selected traffic division, and 14.3% selected patrol. Another 10.7% of respondents chose the "other" category, where they generally entered into the text box that they were a commander or supervisor.

Furthermore, Table 5 shows that 78.3% of the respondents' organizations have a separate division charged with investigating crashes. In response to the question, “Does your organization have a separate division charged with crashes?”, 8.9% of respondents chose the "other" option, and they provided supplemental information in the provided text box. These “other” responses generally indicated that organizations have specialized training or a specialized unit for more serious crashes, but all patrol officers investigate basic crashes. Overall, the respondents represent law enforcement officers, and most investigate crashes. However, the respondents' individual roles, work experiences, and organizational structures vary widely.

The next set of questions relates to the police officers' handling of crash data. As provided in Table 5, a survey question gauges the level of AV training the officers have available to them. Of the 43 responses to this question, only 16.3% indicated they had the opportunity for AV sensor training for crash reconstruction. Nearly one-half of respondents (48.8%) indicated that while they do not currently have a plan for AV training, they expect to have a plan to implement this training in the future. Some respondents (32.2%) indicated no plans to implement this training. Also provided in Table 5, the survey assesses whether officers have access to the processing or managing of crash data. Most respondents (75.5%) answered "yes," with another 20.4% stating that they had a plan for or expected to have a plan for managing crash data.

The next set of questions discusses the use of EDRs. As shown in Table 5, in response to whether officers have used EDRs, 90.2% responded "yes." Next, shown in Table 4, officers were asked what information they received from EDRs, and responses included vehicle speed (97.9%), brake status (89.4%), seatbelt usage (87.2%), throttle position (76.6%), engine RPM (76.6%), steering input (68.1%), and "other" (23.4%). The "other" responses included change in velocity ("delta-V"), friction, and vehicle roll angle ("roll over"). Next, shown in Table 4, the survey asks respondents what level(s) of EDR training they have completed. Only 47.5% of the total survey respondents answered the question. The majority of these respondents (58.6%) had completed EDR technician training, 44.8% completed EDR basic, and 34.5% completed EDR advanced. Another 24.1% of respondents selected "other," which generally indicated that the respondent had completed no EDR training.

A set of questions allows the officers to assess the future of AV data in crash investigations. As provided in Table 4, the officers were asked which information is not usually available today that they would most like to receive from a vehicle following a collision. The majority of officers (54.9%) answered "vehicle and occupant dynamics." Another 31.4% answered "vehicle systems and performance." Also shown in Table 4, another question asks officers which AV data source(s) would provide the most helpful information, and an overwhelming number of officers, 94.1%, selected cameras. A majority of officers also chose GPS (58.8%) and LiDAR (51.0%).

Officers were asked about the perceived barriers to using AV sensor data. As shown in Table 4, a majority of the officers selected "data accessibility and availability" (60.8%) and "budget" (56.9%). Another 9.8% of officers chose "other," which included responses such as "ability to translate complex data to a jury," "lack of training," "getting a search warrant for data," and "ability to validate data in crashes with limited crash evidence." Lastly, as shown in Table 4, officers were queried about how AV sensor data can enhance the crash investigation. The majority selected each of the options: "improved data accuracy" (88.2%), "increased data availability" (82.4%), "improved understanding of human factors" (74.5%), "enhanced vehicle and occupant safety" (56.9%), and "improved understanding of environmental factors" (49.0%).

Overall, the respondents represent well-experienced law enforcement officials who have had experience and training in investigating roadway crashes. Work experiences and roles are diverse, with some respondents working as supervisors or commanders with experience in thousands of crashes, while others have only worked on a few crashes. Similarly, there is also a wide range of technology use and training levels. This diversity is important to consider when creating an AV training curriculum for law enforcement.

Table 3: Survey Respondents - Work Context (Continuous Variables)

Question	Sample Size (N)	Mean	Median	Min	Max	Range
How many sworn officers work in your organization?	56	435.5	137.5	5	1,465	1,460
How many fatal and/or prosecutable crashes have you worked on?	55	160.1	53	0	1,700	1,700

Table 4: Survey Respondents - Work Context (Multiple-Select)

Selection	Checked Percent	Confidence Interval	Checked Count	Sample Size (N)
What is your role in collision investigation? (Select all that apply.)				
Crash Reconstructionist	91.1%	80.7% to 96.1%	51	56
Traffic Division	39.3%	27.6% to 52.4%	22	56
Patrol	14.3%	7.4% to 25.7%	8	56
Other	10.7%	5.0% to 21.5%	6	56
Total	155.4%			
What information have you typically received from the EDR automatically after a collision? (Select all that apply)				
Vehicle Speed	97.9%	88.9% to 99.6%	46	47
Brake Status	89.4%	77.4% to 95.4%	42	47

Selection	Checked Percent	Confidence Interval	Checked Count	Sample Size (N)
Seatbelt Usage	87.2%	74.8% to 94.0%	41	47
Throttle Position	76.6%	62.8% to 86.4%	36	47
Engine RPM	76.6%	62.8% to 86.4%	36	47
Steering Input	68.1%	53.8% to 79.6%	32	47
Other	23.4%	13.6% to 37.2%	11	47
Total	749.5%			
Have you completed any training for EDR data retrieval? If so, please specify which course(s) you have completed.				
EDR Technician	58.6%	40.7% to 74.5%	17	29
EDR Basic	44.8%	28.4% to 62.5%	13	29
EDR Advanced	34.5%	19.9% to 52.7%	10	29
Other	24.1%	12.2% to 42.1%	7	29
Total	162.0%			
Of the available data sources in automated vehicles mentioned, which would provide the most helpful information that is not currently available? (Select all that apply.)				
Cameras	94.1%	84.1% to 98.0%	48	51
Global Positioning System (GPS)	58.8%	45.2% to 71.2%	30	51
LiDAR From Vehicles	51.0%	37.7% to 64.1%	26	51

Selection	Checked Percent	Confidence Interval	Checked Count	Sample Size (N)
Onboard Units (OBUs)	47.1%	34.1% to 60.5%	24	51
Millimeter Wave Radar (MMWR)	27.5%	17.1% to 40.9%	14	51
Infrared	21.6%	12.5% to 34.6%	11	51
Ultrasound	17.6%	9.6% to 30.3%	9	51
Other	3.9%	1.1% to 13.2%	2	51
Total	321.6%			
What are some significant barriers based on your work experience for using automated vehicle sensor data in crash reconstruction? (Select all that apply.)				
Data Availability and Accessibility	60.8%	47.1% to 73.0%	31	51
Budget	56.9%	43.3% to 69.5%	29	51
Data Format and Standardization	45.1%	32.3% to 58.6%	23	51
Data Analysis	37.3%	25.3% to 51.0%	19	51
Technical Complexity	35.3%	23.6% to 49.0%	18	51
Liability and Privacy Concerns	27.5%	17.1% to 40.9%	14	51
Time	21.6%	12.5% to 34.6%	11	51
Other	9.8%	4.3% to 21.0%	5	51
Total	294.12%			

Selection	Checked Percent	Confidence Interval	Checked Count	Sample Size (N)
Based on your work experience, how can automated vehicle sensor data enhance crash investigation? (Select all that apply.)				
Improved Data Accuracy	88.2%	76.6% to 94.5%	45	51
Increased Data Availability	82.4%	69.7% to 90.4%	42	51
Improved Understanding of Human Factors	74.5%	61.1% to 84.5%	38	51
Enhanced Vehicle and Occupant Safety	56.9%	43.3% to 69.5%	29	51
Improved Understanding of Environmental Factors	49.0%	35.9% to 62.3%	25	51
Other	2.0%	0.3% to 10.3%	1	51
Total	352.9%			

Table 5: Survey Respondents - Work Context (Multiple-Choice)

Choice	Count	Percent of Data	Confidence Interval (Percent of Data)	Sample Size (N)
Does your organization have a separate division charged with investigating crashes?				
Yes	36	78.30%	64.4% to 87.7%	56
No	7	12.5%	6.2% to 23.6%	56
Other	5	8.9%	3.9% to 19.3%	56
Total	56	100%		

Choice	Count	Percent of Data	Confidence Interval (Percent of Data)	Sample Size (N)
Has your organization provided the opportunity for training on the use of automated vehicle sensor data for crash reconstruction purposes?				
Yes	7	16.3%	8.1% to 30.0%	43
No, but we have a specific plan to implement this training	1	2.3%	0.4% to 12.1%	43
No, but we expect to have a specific plan to implement this training in the future	21	48.8%	34.6% to 63.2%	43
No, and we do not plan to implement this training	14	32.6%	20.5% to 47.5%	43
Total	43	100%		
Does your organization have access to the processing or managing of crash data from vehicles involved in a collision?				
Yes	37	75.5%	61.9% to 85.4%	49
No, but we have a specific plan for this	3	6.1%	2.1% to 16.5%	49
No, but we expect to have a specific plan for this in the future	7	14.3%	7.1% to 26.7%	49
No, and we don't plan for this	2	4.1%	1.1% to 13.7%	49
Total	49	100%		
Have you ever used Event Data Recorders (EDRs) for collision investigation?				
Yes	46	90.2%	79.0% to 95.7%	51
No	5	9.8%	4.3% to 21.0%	51
Total	51	100%		

Choice	Count	Percent of Data	Confidence Interval (Percent of Data)	Sample Size (N)
Thinking of the future of collision investigation, what information (not usually available today) would you most like to get from a vehicle automatically after a collision?				
Vehicle and occupant dynamics	28	54.9%	41.4% to 67.7%	51
Environmental data	5	9.8%	4.3% to 21.0%	51
Vehicle systems and performance	16	31.4%	20.3% to 45.0%	51
Other	2	3.9%	1.1% to 13.2%	51
Total	51	100%		

Crash Investigation Practices by Officers

The next set of questions relates to crash investigations and asks officers to evaluate a series of statements on a 5-point Likert scale. Respondents were asked about how six different aspects of collision investigation are fulfilled in the current process, as shown in Table 6. The six statements are as follows:

1. Accuracy and reliability of collision investigation
2. Improvement of safety and mitigation of future collisions
3. Efficiency and speed of collision investigations
4. Data availability during collision investigations
5. Standardization of how collisions are investigated
6. Training and certification for collision investigation

The majority of respondents chose "adequate" for all six of the statements. However, "training and certification for collision investigation," "standardization of how collisions are investigated," and “accuracy and reliability of collision investigation” each received 12% “inadequate” responses. “Accuracy and reliability of collision investigations” was the most positively rated aspect, with a majority (56%) of ratings as “adequate” and another 22% of ratings as “excellent.” Both “efficiency and speed of collision investigations” and “data availability during collision investigations” received varied responses, with most respondents ranking these aspects as “somewhat adequate” or “adequate.”

The survey also asks officers to rank their familiarity with seven different AV technologies, which are as follows:

1. Global positioning system (GPS)
2. Onboard units (OBUs)
3. Millimeter wave radar (MMWR)
4. Ultrasound sensors
5. Infrared sensors
6. Light detection and ranging (LiDAR)
7. Cameras

As shown in Table 7, a majority of officers responded that they were not at all familiar with MMWR (64.7%), ultrasound (60.8%), or infrared sensors (54.0%). Another large percentage (41.2%) indicated that they were not at all familiar with OBUs. However, officers stated they were moderately familiar (51.0%) or extremely familiar (5.9%) with cameras.

The officers were also queried about their familiarity with ten different advanced driver assistance systems (ADAS) technologies, which are as follows:

1. Adaptive cruise control (ACC)
2. Lane departure warning (LDW)
3. Blind spot monitoring (BSM)
4. Rear cross-traffic alert (RCTA)
5. Forward collision warning (FCW)
6. Automatic emergency braking (AEB)
7. Park assist
8. Night vision
9. Head-up display
10. Driver monitoring systems (DMSs)

As Table 7 shows, a large percentage indicated that they were not at all familiar with rear cross-traffic alert (45.1%) or night vision (40.0%). Officers were most familiar with blind spot monitoring, with 11.8% ranking the technology as “extremely familiar.” Many officers were also familiar with adaptive cruise control, lane departure warning, and forward collision warning, with 33.3% of officers ranking each of these technologies as “moderately familiar.”

Lastly, the survey asks officers to rate their familiarity with different AV training topics, which are as follows:

1. Understanding AV technology: This includes training on how AVs work, the different sensors and systems used to drive the vehicle, and the communication protocols used by AVs to interact with other vehicles (V2V) and infrastructure (V2I).
2. Legal and ethical considerations: Law enforcement personnel need to be aware of the legal and ethical implications of AVs, including privacy, security, and liability issues.
3. Traffic enforcement and regulation: With the increasing use of AVs, law enforcement personnel must be trained in how to enforce traffic regulations and respond to incidents involving AVs.

4. Incident response and crash investigation: Law enforcement personnel will need to be trained on how to respond to and investigate incidents involving AVs, including collecting and preserving evidence and interacting with AV manufacturers during an investigation.
5. Cybersecurity: As AVs rely on complex systems and networks, law enforcement personnel need to be trained on the various cybersecurity risks and threats to CAVs, and how to respond to cyber attacks.
6. Human factors: Law enforcement personnel need to understand the impact that CAVs may have on human behavior, such as changes in driver behavior, and how to address related safety concerns.
7. Communication and community engagement: Law enforcement personnel need to be trained on how to communicate and engage with communities about the benefits and risks associated with AVs, and how to address public concerns and misconceptions about the technology.

As provided in Table 7, the topics that were most rated as “not at all familiar” among respondents are "understanding automated vehicle technology" (66.7%), “cybersecurity” (66.7%), and “communication and community engagement” (51.0%). None of the topics received a significant percentage of “extremely familiar” ratings. However, officers indicated moderate familiarity with “legal and ethical considerations” (14.0%) and “incidence response and crash investigation” (11.8%).

Table 6: Respondent Rankings of the Adequacy of Current Collision Investigation Practices

	Very inade-quate	Inade-quate	Some-what adequate	Adequate	Excellent	Total
Accuracy and reliability of collision investigations (N = 50)	2.0%	0.0%	20.0%	56.0%	22.0%	100%
Improvement of safety and mitigation of future collision investigations (N = 50)	0.0%	8.0%	46.0%	40.0%	6.0%	100%
Efficiency and speed of collision investigations (N = 50)	0.0%	8.0%	34.0%	46.0%	12.0%	100%
Data availability during collision investigations (N = 50)	0.00%	12.0%	38.0%	44.0%	6.0%	100%
Standardization of how collisions are investigated (N = 50)	2.0%	12.0%	30.0%	48.0%	8.0%	100%
Training and certification for collision investigation (N = 50)	2.0%	10.0%	28.0%	46.0%	14.0%	100%

Table 7: Respondent Rankings of Familiarity with Technologies and Training Topics

	Not at all familiar	Slightly familiar	Somewhat familiar	Moderately familiar	Extremely familiar	Total
Automated Vehicle Sensors						
Global Positioning System (GPS) (N = 51)	3.9%	23.5%	15.7%	51.0%	5.9%	100%
Onboard Units (OBUs) (N = 51)	41.2%	33.3%	13.7%	51.0%	0.0%	100%
Millimeter Wave Radar (MMWR) (N = 51)	64.7%	25.5%	9.8%	51.0%	0.0%	100%
Ultrasound Sensors (N = 51)	60.8%	25.5%	7.8%	51.0%	0.0%	100%
Infrared Sensors (N = 50)	54.0%	28.0%	10.0%	51.0%	0.0%	100%
LiDAR (N = 51)	33.3%	27.5%	15.7%	51.0%	2.0%	100%
Cameras (N = 51)	3.9%	15.7%	15.7%	51.0%	5.9%	100%
Advanced Driver Assistance Systems						
Adaptive Cruise Control (ACC) (N = 51)	13.7%	17.6%	25.5%	33.3%	9.8%	100%
Lane Departure Warning (LDW) (N = 51)	13.7%	15.7%	27.5%	33.3%	9.8%	100%
Blind Spot Monitoring (BSM) (N = 51)	17.6%	13.7%	19.6%	37.3%	11.8%	100%
Rear Cross-Traffic Alert (RCTA) (N = 51)	45.1%	11.8%	19.6%	19.6%	3.9%	100%
Forward Collision Warning (FCW) (N = 51)	11.8%	23.5%	23.5%	33.3%	7.8%	100%
Automatic Emergency Braking (AEB) (N = 51)	19.6%	21.6%	19.6%	29.4%	9.8%	100%
Park Assist (N = 51)	15.7%	39.2%	11.8%	25.5%	7.8%	100%
Night Vision (N = 50)	40.0%	30.0%	14.0%	14.0%	2.0%	100%
Head-Up Display (N = 50)	22.0%	30.0%	16.0%	24.0%	8.0%	100%
Driver Monitoring Systems (DMS) (N = 51)	23.5%	33.3%	23.5%	17.6%	2.0%	100%
Training Topics						
Understanding automated vehicle technology (N = 51)	66.7%	23.5%	7.8%	2.0%	0.0%	100%

	Not at all familiar	Slightly familiar	Somewhat familiar	Moderately familiar	Extremely familiar	Total
Legal and ethical considerations (N = 51)	36.0%	32.0%	16.0%	14.0%	2.0%	100%
Traffic enforcement and regulation (N = 51)	45.1%	27.5%	21.6%	5.9%	0.0%	100%
Incident response and crash investigation (N = 51)	41.2%	35.3%	11.8%	11.8%	0.0%	100%
Cybersecurity (N = 51)	66.7%	23.5%	9.8%	0.0%	0.0%	100%
Human factors (N = 51)	39.2%	43.1%	11.8%	5.9%	0.0%	100%
Communication and community engagement (N = 51)	51.0%	29.4%	15.7%	3.9%	0.0%	100%

Qualitative Information Provided by Respondents

Throughout the questionnaire, short answer questions allow the respondents to provide their thoughts via text entry. Because of the varying responses, text analytic methods are preferable to traditional descriptive statistics. The first answer is to a question asking respondents if they have ever used vehicle camera footage in a crash investigation, and if so, how this footage affected their investigation. The comments were defined by the following topics:

1. Have used cameras: Comments indicating the respondent has used video camera footage for crash investigation.
2. Never used cameras: Comments indicating that the respondent has never used video camera footage.
3. Confirming evidence: Comments indicating that video camera footage was able to confirm evidence collected by other means during the crash investigation.
4. Conflicting evidence: Comments indicating that video camera footage was able to refute evidence collected by other means, such as witness statements.
5. New data: Comments indicating that video camera footage brought new data or evidence to the investigation.
6. Prosecution/fault: Comments indicating that video camera footage was used to help with prosecution or determine fault during a crash.
7. Surveillance footage: Comments indicating that video camera footage in the form of surveillance cameras has been used in a crash investigation.
8. Aftermarket cameras: Comments indicating that video camera footage in the form of aftermarket dashboard cameras has been used in a crash investigation.

The number of comments discussing each of these topics is provided in Table 8, and a word cloud generated in Qualtrics from these comments is shown in Figure 3. More comments indicated that they had used cameras (67.39%) than those that had not (26.09%), and almost a quarter (23.91%) of the comments indicated that the cameras brought new data that was not available through other means during crash investigations. The word cloud shows that words such as “determine”, “fault”, “speed”, “evidence”, and “help” are common among the comments, indicating that video cameras have provided valuable evidence to many officers during crash investigations.

The survey asked officers if they used in-vehicle LiDAR and radar in a crash investigation. The question regarding LiDAR received 49 responses, and the question regarding radar received 48 replies. All comments discussing LiDAR indicated that the officers have not used in-vehicle LiDAR for a crash investigation. Nearly all responses discussing radar indicated that in-vehicle radar had not been used for a crash investigation. However, one comment stated that in-vehicle radar was used to pull vehicle information to confirm investigation information. Another question asks officers to list which tools they typically use in a crash investigation. Responses were varied, and comments were sorted into topics as follows:

1. EDR: Comments including electronic data recorders (EDRs).
2. Drone photography: Comments including drones or drone footage.
3. Total station: Comments including total stations. The makes of total stations mentioned include Leica, Carlson, Nikon, and Faro.
4. Infotainment data: Comments including infotainment data or mention of an infotainment data tool, such as the Berla system tool.
5. Digital camera: Comments mentioning the use of a digital camera.
6. EDR retrieval equipment: Comments mentioning the use of EDR retrieval equipment, such as the Bosch Crash Data Retrieval Tool.
7. 3D laser scanner: Comments mentioning the use of a 3D laser scanner. The Faro 360 scanner is commonly referenced.
8. GPS/Global navigation satellite system (GNSS): Mentions of either GPS or GNSS rovers. Leica is a common make for rovers referenced.
9. Modeling software: Comments include modeling software such as Crashzone, Pix4D, Cyclone, and IMS Map360.
10. Traffic camera: Comments mentioning the use of traffic cameras such as Redflex cameras.
11. Crash simulation software: Comments that mention crash simulation software such as Virtual Crash (VCrash).
12. Dash camera: Comments that mention the use of dashboard cameras.
13. Motion performance instruments: Comments that mention the use of motion performance instruments such as Vericom tools and friction testing devices.
14. Crash database: This includes comments mentioning crash databases such as TITAN.
15. Outsourcing: Comments that indicate that an organization relies on outside sources, such as the Tennessee Highway Patrol, for crash analysis due to a lack of equipment or other resources.

The most prevalent answers were Total Stations (76.09%), EDR (67.39%), and Drones (69.57%). Figure 4 is a word cloud of these answers generated by Qualtrics, which revealed that “rover,” “scanner,” and “camera” also emerge as commonly mentioned tools.

Table 8: Topics Discussed by Respondents

Question	Topic	Count	Percentage
Have you ever used vehicle camera footage during a crash investigation? If so, how did this footage impact the process and outcome of the investigation? (N =49)	Never used cameras	12	26.09%
	Have used cameras	31	67.39%
	Confirming evidence	8	17.39%
	Conflicting evidence	1	2.17%
	New data	11	23.91%
	Prosecution/fault	10	21.74%
	Surveillance footage	2	4.35%
	Aftermarket cameras	4	8.70%
	Total		171.74%
What software or other tools do you typically use during a crash investigation (e.g., Analysis and Simulation Software, Total Stations, Drone Cameras, Event Data Recorders)? (N = 46)	EDR	31	67.39%
	Drone Photography	32	69.57%
	Total Station	35	76.09%
	Infotainment Data	9	19.57%
	Digital Camera	3	6.52%
	EDR Retrieval Equipment	5	10.87%
	3D Laser Scanner	15	32.61%
	GPS/GNSS	13	28.26%
	Modeling Software	8	17.39%
	Traffic Camera	1	2.17%
	Crash Simulation Software	8	17.39%
	Dash Camera	1	2.17%

Question	Topic	Count	Percentage
	Motion Performance Instruments	2	4.35%
	Crash Database	1	2.17%
	Outsourcing	2	4.35%
	Total		360.87%

Figure 3: Word Cloud of Video Camera Footage in Crash Investigations

Figure 4: Word Cloud of Equipment Used in Crash Investigations

The survey asks officers whether they have completed AV data retrieval training. Of the 42 comments, 37 answered "No," three mentioned EDR training, one mentioned infotainment training, and one said a Berla system training. With these responses, it can be reasonably assumed that no officers have received any AV-specific training. Notably, this question was directed at determining if any officers have received AV training.

Officers were asked open-ended questions about providing their thoughts on what could be improved in collision investigations and if there is anything else they would like to mention about the subject of the questionnaire. The comments provided were highly informative and comprehensive, and instead of summarizing them into simplistic descriptions, select comments are presented in their entirety in Tables 9 and 10. Note: comments such as “N/A” or “No” are not included in these tables.

The comments generally emphasized the need for more standardized, State-funded crash investigation training and certification. The comments regarding the current process of collision investigation (Table 9) emphasize the need for standardized EDRs across vehicle manufacturers, comprehensive data captured from smart vehicles, training in new technologies, and increased availability of crash investigation classes. The final thoughts from the respondents (Table 10) highlight the need for improved understanding and access to evidence in AV crash investigations, emphasizing the importance of additional training and updated technology. Some respondents expressed concerns about the effect of driver-assistance systems on human behavior and the legal implications of AV crashes. State assistance is requested due to budget constraints, with a focus on advanced training and diverse crash instruction classes. Analysis skills are deemed essential alongside data retrieval. Word clouds for each question were created, as shown in Figures 5 and 6, both of which include the word “training” as a central theme of the responses.

Table 9: Respondent Comments Regarding the Current Process of Collision Investigation

Is there anything else that could be improved about the current process of collision investigation? (N =27)
“More standardization between vehicle manufacturers on EDRs.”
“Capturing all available relevant data from ‘smart’ vehicles would certainly improve the quality and efficiency of crash investigations.”
“Uniformity of EDR output image and uniformity of EDR connections for download.”
“I love having EDR data; however, I'm concerned about how many departments think EDR data alone replaces mathematical analysis.”
“Just more up to date training that relates to the newer technology that has come out over the years.”
“Could always use more training, especially in the newest technologies.”
“More access to training on the advanced systems in newer vehicles. The current crash investigation training relies on old standards and processes. Things we are taught, such as measuring skid marks, are rarely seen in our current crashes due to advancements in vehicle technology.”
“Taking the data collection to writing a report.”
“Basic collision investigation and reconstruction has to be taken back to the roots. We are often times too dependent upon electronic data and forget the skills of reconstructing the crashes by hand. While sometimes the basics seem boring, it is necessary to build the foundation and then build the advanced processes on top.”
“Working to get drone mapping software to eliminate the need for multiple LEICA scans. This will allow us to open roadways faster and get our people off the scene as fast as possible.”

Is there anything else that could be improved about the current process of collision investigation? (N =27)
“More crash investigation classes to be offered through the State to help get Agencies caught up.”
“A standardized certification process for crash reconstruction re-certification statewide, in TN.”
“More training of officers to be crash investigators, and sending more people to EDR training.”

Table 10: Final Thoughts from Respondents

Do you have any final thoughts regarding crash investigation, automated vehicle or advanced driver-assistance system technology, or other related topics? (N =16)
“With the national trend of automated vehicles being purchased and driven, there is a need for deeper understanding and knowledge of how these vehicles operate.”
“This is an area for great advancement in crash investigation that has not been widely conveyed to law enforcement. Useful evidence is being missed because we are unaware of its presence or don't have the ability to access it.”
“We definitely need more training.”
“I wonder, with the increasing amount of driver-assistance systems, is this going to have an adverse effect on human behavior? People used to actually DRIVE a car especially before automatic driving systems (as opposed to manually shifting gears.) Will our understanding of human factors need to be adjusted? What will this do to traditional concepts of perception/reaction? Will the decided sensitivity settings play a part in court? If I have an automatic vehicle and I don't like it braking for every piece of debris that flies around and I turn the sensitivity to the lowest setting, and my car strikes a pedestrian which I did not react to, how will this relate to criminal culpability? And again, how do I get a search warrant for data secured in California (for example) and the crash occurred in Georgia?”
“Just that we are behind the curve on this technology and need training. We need the software technology to retrieve the data. Most crash investigation is outdated when it comes to the new vehicle safety features that are in effect today.”
“Thank you for doing the survey and research. I believe that most officers are doing the best they can to investigate crashes and determine the factors that caused them. In many cases, lack of training and access to proper equipment ensures that some data is lost. Standardizing some of the training and ensuring access to the latest technology would allow for improved investigations.”
“This information would be very useful in investigating crashes and educating the public.”
“Any assistance in training that can be provided by the State would be extremely beneficial. We are behind the curve on dealing with crashes involving these complex vehicles. We do not have the budget to get our Investigators trained on this new technology.”
“We need more advanced training for the circumstances that we are dealing with today.”
“New field - cannot think of any fatal collisions in recent years involving this technology.”
“I would like to see a larger variety of crash instruction classes offered throughout the state.”

Do you have any final thoughts regarding crash investigation, automated vehicle or advanced driver-assistance system technology, or other related topics? (N =16)
“Officers need to understand that obtaining data is not the be all end all. There must be training provided to teach analysis of all data sources. Currently, too many agencies pull EDR data but provide no or inadequate analysis.”
“Would like to see some training for these topics in the future. Thanks!”

Figure 5: Word Cloud of the Current Investigation Process

Figure 6: Word Cloud of Final Thoughts

Factor Analysis

Factor Analysis is a popular analytic technique to reduce high dimensional data into a set of distinct factors that explain the most variation in the data and reveal the underlying relationship between key variables. Fifteen variables, mostly relevant to the familiarity level of crash investigation agencies’ officers with AV technology, potential data sources for AV crash investigation, and level of adequacy of current crash investigation procedures, were extracted from the survey responses for an exploratory factor analysis. Missing values in each variable were replaced with the mean of the available values. The final dataset consisted of 15 variables, with 61 entries in each variable. The number of distinct factors was selected according to Keiser's rule, which states that only the factors with Eigenvalues greater than one can be considered distinct factors. Results of the factor analysis indicate that four out of the 15 factors had eigenvalues greater than one. The selected factors are as follows: (1) "Digital forensics integration for AV crash reconstruction," (2) "AV crash data management and investigation standards," (3) "AV crash investigation efficacy and safety assurance," and (4) "Advanced training in AV crash investigation." The factors point to the criticality of AV data management and proper training of crash investigators. Figure 7 presents the association of variables with their respective factors through loading values.

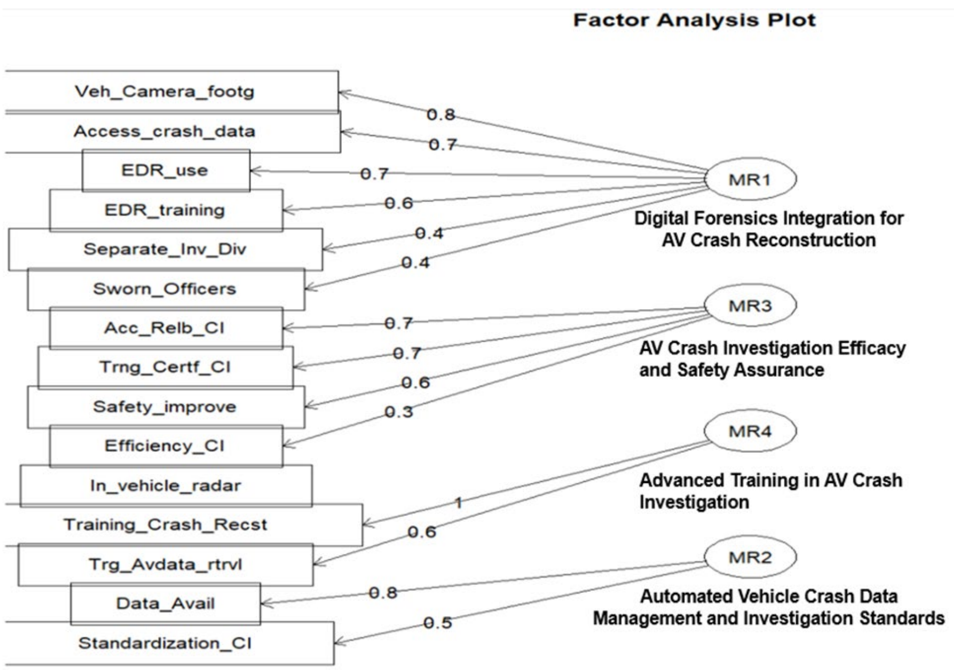

Figure 7: Factor Analysis Plot

Discussion

This survey aims to answer two key research questions:

1. What pertinent information or processes are lacking in crash investigations?
2. How can law enforcement be prepared to use AV data in crash investigations?

First, discussing question one, the survey highlights several gaps in the current process of collision investigation. Respondents indicated a need for more standardization in EDR training and connections for downloading data. Further, respondents indicated that vehicle and occupant dynamic information, which is not usually available today, would be most valuable after a collision. Vehicle and occupant dynamics include information such as vehicle trajectory or driver behavior, and cameras or other AV sensors provide this information. Furthermore, both data availability and data format were significant barriers to crash reconstruction. While AV sensors can provide a robust dataset for crash investigation, accessing this information from sensors and AV manufacturers may be more challenging. Respondents also indicate the efficiency and speed of collision investigations could be improved. Access to the information provided by AV sensors and cameras can allow for more efficient crash investigations by depicting a clearer image of crash events.

The value of vehicle camera footage as a data source for crash investigation emerges as a theme in the responses to multiple survey questions. Out of each AV sensor, cameras are the most valuable and familiar to the officers. Many respondents already have experience using cameras during a crash investigation, whether through surveillance cameras, aftermarket dashboard cameras, or AV cameras. Further, cameras in the form of drones and digital cameras are often used during crash investigations to capture the crash scene accurately. The comments provided by respondents show that cameras greatly enhance crash investigations in many ways, such as determining crash sequences, providing culpability evidence, and confirming speed calculations. With the growing prevalence of interior and exterior cameras in modern vehicles, the abundance of crash footage will significantly augment the available information to crash investigators.

Question two asks how law enforcement can be better prepared to use AV data in crash investigations, and this study responds by providing a list of training topics. The need for additional training is emphasized throughout the multiple-choice and short-answer responses. Specific areas of unfamiliarity include understanding AV technology, cybersecurity, communication and community engagement, and traffic enforcement. The following list of training topics, shown in Table 11, has been curated based on survey results. While an understanding of all of these training topics is pertinent, they are prioritized both by respondents' unfamiliarity and the potential to advance crash investigation.

Table 11: List of Training Topics

Number	Topic	Description
1	Understanding Automated Vehicle Technology	This is a broad topic that includes multiple facets of learning, including what sensors are used in different makes and models of automated vehicles, what data can be collected from these sensors, and how this new technology can affect human and roadway factors. According to the survey, the most unfamiliar automated vehicle technologies are ultrasound sensors, MMWR, infrared sensors, and OBUs. Cameras and GPS are both relatively familiar to survey respondents; however, it is necessary to train officers to access the cameras and GPS sensors equipped in automated vehicles.
2	Accessing Automated Vehicle Data	Accessing automated vehicle sensor data may require coordination with vehicle manufacturers and the use of data retrieval equipment. Crash investigators must be properly trained in the processes by which data is retrieved.

Number	Topic	Description
3	Applying Automated Vehicle Sensor Data to Crash Investigation	Once data is retrieved, crash investigators must be trained in how to properly analyse and apply crash data as evidence. This will require familiarity with handling multiple data types from various sensors and using different software programs for analysis.
4	Cybersecurity Concerns	While automated vehicles can increase safety and mobility, automated vehicles can be subjected to cybersecurity threats, which introduces new hazards on the roadways. Crash investigators must be made aware of these threats and learn how to properly mitigate and respond to cybersecurity concerns.
5	Traffic Enforcement and Regulation	Automated vehicles operate differently than conventional vehicles, which may lead to shifting traffic enforcement and regulation practices in the near future. Law enforcement will need to be trained in local traffic regulations regarding AVs.
6	Communication and Community Engagement	Law enforcement, once trained in automated vehicle technology, should also be trained in how to raise public awareness of new AV technology, regulations, and potential risks.
7	Legal and Ethical Implications	Automated vehicles introduce new driver-vehicle relationships to the roadway, and with these shifting relationships, the ethical and legal landscape also evolves. It is not always immediately clear how all automated vehicle crashes should be handled and who should be faulted for a crash. Therefore, crash investigators should be trained in the ethical and legal principles that guide crash culpability.

Limitations

This study is not without limitations. Although the study is spatially constrained to Tennessee, it provides valuable and context-specific insights that can serve as a foundation for future comparative research and dialog. Having said this, the results may not be generalizable to other States or jurisdictions with differing crash investigation procedures. Examining crash investigation practices across different States or a larger geographical extent can yield more meaningful insights into the AV technology literacy and specific needs of the crash investigative agencies relevant to CAV crash investigation. Furthermore, the survey of crash investigators has a small sample size, meaning that a larger sample will be needed for more robust results. The methodology of this survey can be reproduced in future studies with a larger sample size to allow for more generalizable results.

Conclusion

This survey of 61 crash investigators in law enforcement in Tennessee revealed valuable insights about how crash investigation can be advanced using AV sensor data. The respondents indicated a need for standardization in data retrieval processes, and many comments expressed a demand for State-funded training regarding AV data. Vehicle and occupant dynamics are the most requested information currently lacking in crash investigations, and AV sensors can provide this information. Guidance on the appropriate training for law enforcement is provided, with the most pertinent topics being a comprehensive understanding of various AV sensors and their uses and how to access this data from manufacturers using the necessary equipment. Furthermore, the results from factor analysis also emphasize the need for the integration of digital data provided by CAV sensors, specialized and sophisticated training of crash investigative officers, and adopting standardized protocols for CAV crash investigation to improve its efficiency and effectiveness. Future research can include follow-up surveys that assess whether any of the suggested training has been implemented and if there is an improvement in AV technology literacy among crash investigators.

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Appendix: Law Enforcement Questionnaire

We ask you to be in this research study because you work in law enforcement and have worked in crash investigation in some capacity. You must be age 18 or older to participate in the study. The consent form information will help you decide if you want to be in this research study. Please take your time reading this form and contact the researcher(s) to ask questions if there is anything you do not understand.

Why is the research being done?

The purpose of the research study is to collaborate with law enforcement to identify training needs on the topic of automated vehicle technology and develop a list of training topics. This study is being conducted by researchers at the University of Tennessee, Knoxville. The research team member or University has no financial conflict of interest or other types of conflict of interest (e.g., the researcher is the participants' instructor, supervisor, health care provider, other service providers, etc.).

What will I do in this study?

If you agree to be in this study, you will complete an online survey. The survey includes questions about your work experience, training, and needs, current access to crash data, and areas where crash investigation can be improved. It should take you about 15 to 20 minutes. You can skip questions that you do not want to answer.

Can I say "No"?

Being in this study is up to you. You can stop any time until you submit the survey. After you submit the survey, we cannot remove your responses because we will not know which responses came from you. Either way, your decision won't affect your employment.

Are there any risks to me?

We don't know of any risks to you from being in the study.

Are there any benefits to me?

We do not expect you to benefit from being in this study. Your participation may help us learn more about training needs regarding automated vehicle data in crash investigation. We hope the knowledge gained from this study will be used to produce new and essential training curriculum. What will happen with the information collected for this study?

The survey is anonymous, and no one will be able to link your responses back to you. Your responses to the survey will not be linked to your computer, e-mail address, or other electronic identifiers. Please do not include your name or other information that could be used to identify you in your survey responses. Information provided in this survey can only be kept as secure as any other online communication. Information collected for this study will be published and possibly presented at scientific meetings.

Will I be paid for being in this research study?

You will not be paid for being in this study.

Who can answer my questions about this research study?

If you have questions or concerns about this study or have experienced a research-related problem or injury, contact the researchers.

1) Asad J. Khattak, E-mail: akhattak@utk.edu, Phone: 865-974-7792,

2) Meredith King, E-mail: mking63@vols.utk.edu, Phone: 615-631-0286,

3) Muhammad Adeel, Email: madeel1@vols.utk.edu, Phone: 865-371-5740

4) Sheikh Muhammad Usman, Email: susman1@vols.utk.edu, Phone: 865-236-6995

For questions or concerns about your rights or to speak with someone other than the research team about the study, please contact:

Institutional Review Board
The University of Tennessee, Knoxville
1534 White Avenue
Blount Hall, Room 408
Knoxville, TN 37996-1529
Phone: 865-974-7697
E-mail: utkirb@utk.edu

Statement of Consent
I have read this form and been given a chance to ask questions and have my questions answered. If I have more questions, I have been told who to contact. By selecting “I Agree” below, I am providing my signature by electronic means and agree to be in this study. I can print or save a copy of this consent information for future reference. If I do not want to be in this study, I can select “I Do Not Agree” to exit the survey.

○ I agree to participate (1)

○ I do not agree to participate (2)

Skip To: End of Survey If Statement of Consent I have read this form and been given a chance to ask questions and have my q... = I do not agree to participate

Page Break

End of Block: Block 2

Start of Block: Orientation

The Collaborative Sciences Center for Road Safety (CSCRS) is exploring how new automated vehicle data can be used in crash reconstruction and seeks your help in this regard.

Current accident reconstruction practices rely heavily on event data recorder (EDR) data. EDRs typically provide information such as vehicle speed, brake status, throttle position, steering input, seatbelt status, and occupant detection. Some EDRs include anti-lock braking system (ABS) activity, stability control status, the time between events, tire pressure warning lamp information, gear selector position, and vehicle roll angle.

We are interested in your views on using data from new vehicle technologies like adaptive cruise control and lane departure warnings to assist with accident reconstruction. These systems are designed to assist the driver. They also collect detailed data about the vehicle and surrounding objects that could be useful for collision reconstruction. As technology advances, new information about the vehicle, its location, the environment, and even the driver can be collected.

Background (optional)

Automated vehicles (AVs) have several sensors, including global positioning systems (GPS), onboard units (OBUs), cameras, radar, LiDAR, infrared, and ultrasound. A brief description of each sensor is presented below.

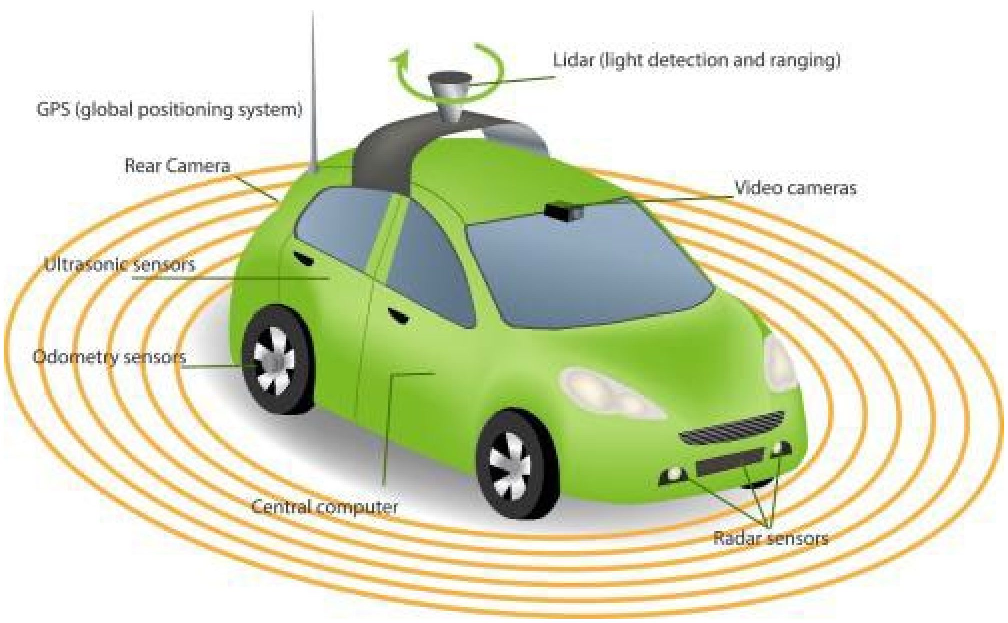
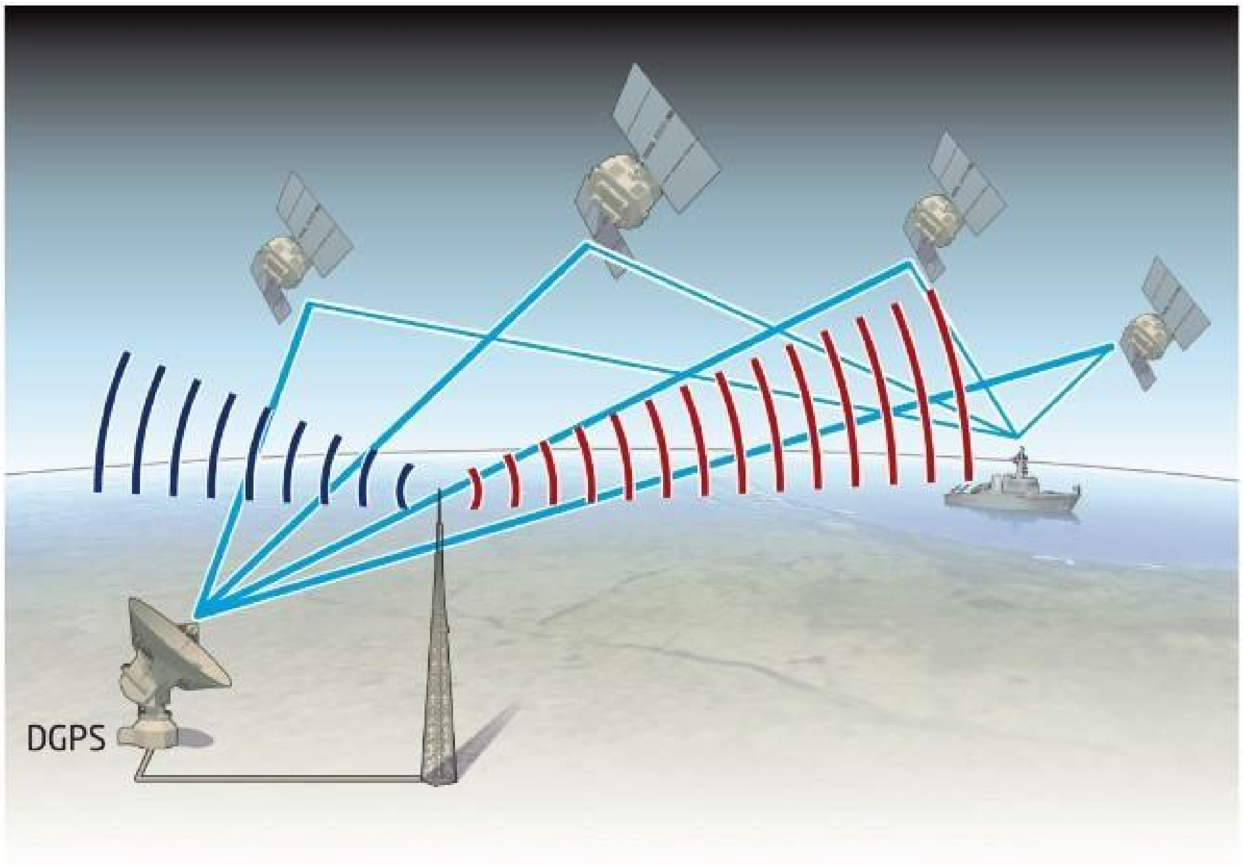


Figure 1: Automated Vehicle Sensors https://innovationatwork.ieee.org/lidr-is-the-latest-game-changing-advancement-for-autonomous-vehicles/

GPS sensors can detect position and speed information including linear acceleration, including linear acceleration, angular velocity, and real-time position data. Limitations of GPS include a slow update rate and an inability to work correctly in the presence of obstacles that block atmospheric signals. GPS is also susceptible to atmospheric errors, refraction, multipath errors, and satellite clock errors.



Shellito, *Introduction to Geospatial Technologies*, 5e, © 2020 W. H. Freeman and Company

Figure 2: GPS

OBUs are another data source within CAVs and are used as a communication tool along with roadside units (RSUs) and short-range communications devices. OBUs collect data from individual sensors within CAVs and send out basic safety messages (BSMs) that are used to communicate with other vehicles (V2V) and the infrastructure (V2I). BSMs help understand the behavior of other drivers. OBUs communicate information such as collision warnings, pathfinding, merge assistance, and speed suggestions. However, a limitation is that OBUs and GPS are vulnerable to cybersecurity attacks.

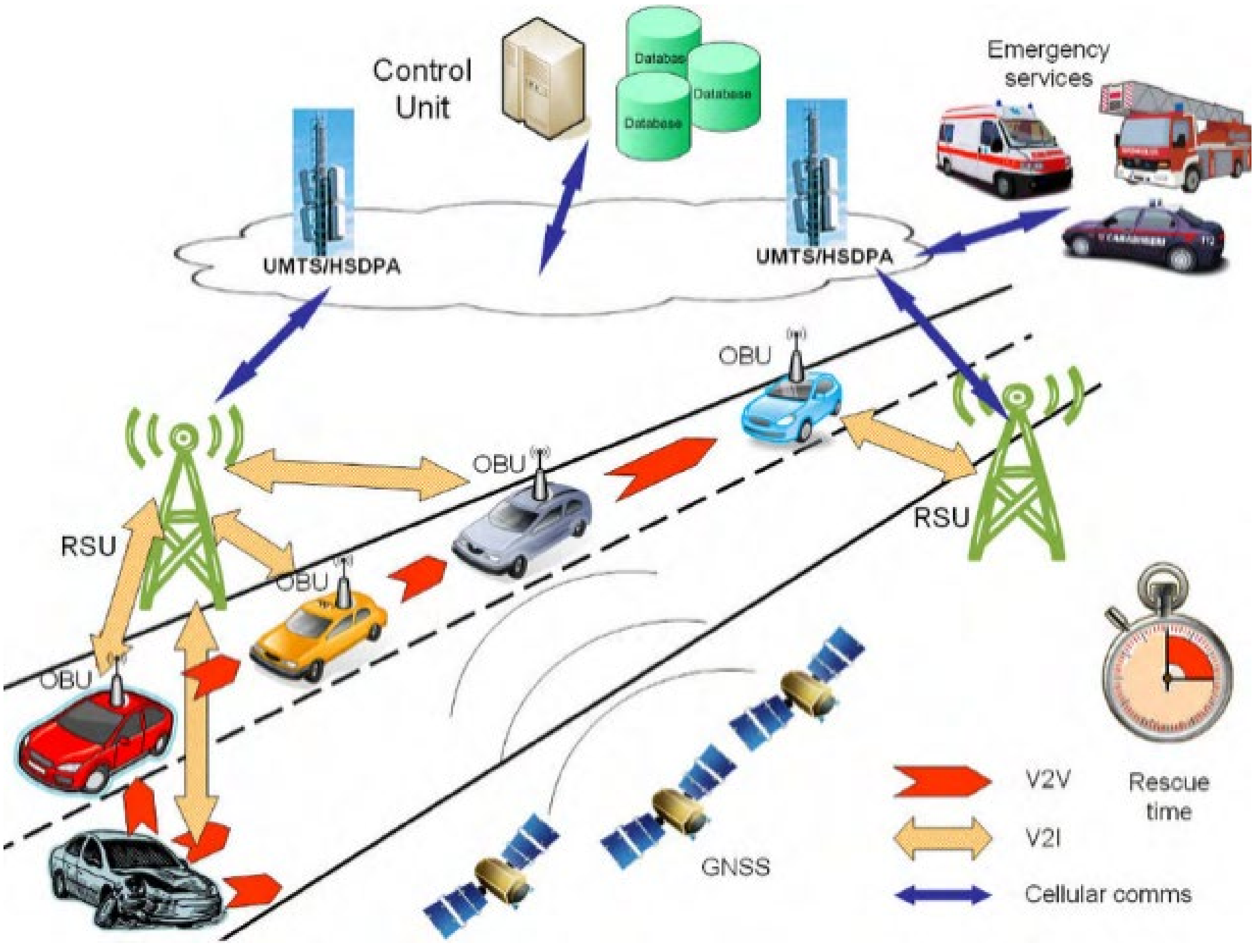


Figure 3: Onboard Units Facilitating V2V and V2I Interactions (3)

CAVs use millimeter wave radar (MMWR) to detect obstacles, roadways, and pedestrians. Radar is robust in most types of extreme weather; however, it exhibits low capability for detecting lateral movement. Radar is also known for its poor resolution, making detecting some stationary objects and pedestrians unreliable.

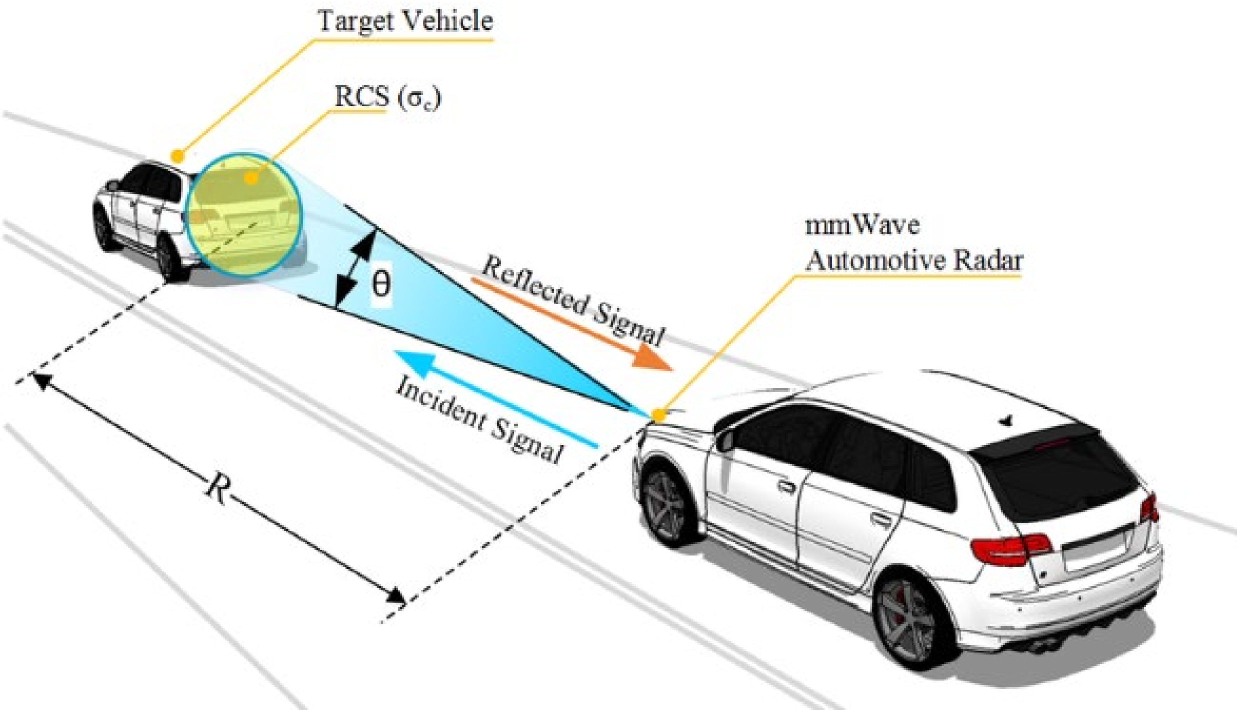


Figure 4: MMWR (4)

Ultrasound sensors use sound waves to detect objects and pedestrians. Ultrasound sensors lack robustness when seeing various types and colors of clothing due to varying degrees of reflection. Ultrasound sensors can also present issues distinguishing the echoes of obstacles and other interfering signals.

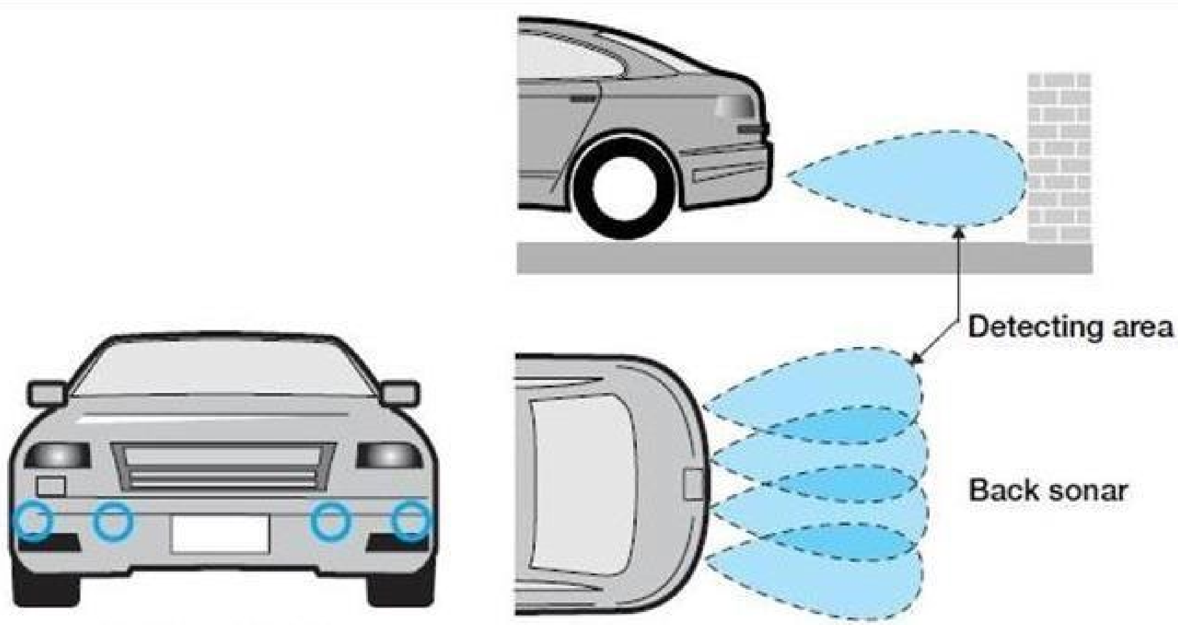


Figure 5: Ultrasound Sensors https://blog.seakexperts.com/self-driving-cars-expert-witness-physics-drives-the-technology/

CAVs also use infrared sensors for pedestrian and vehicle detection. Unlike ultrasound sensors, infrared sensors are robust while detecting pedestrians with different kinds and colors of clothing. Noise created by the surrounding environment and different illumination and temperature conditions may interfere with the detection functionality of the IR sensor.

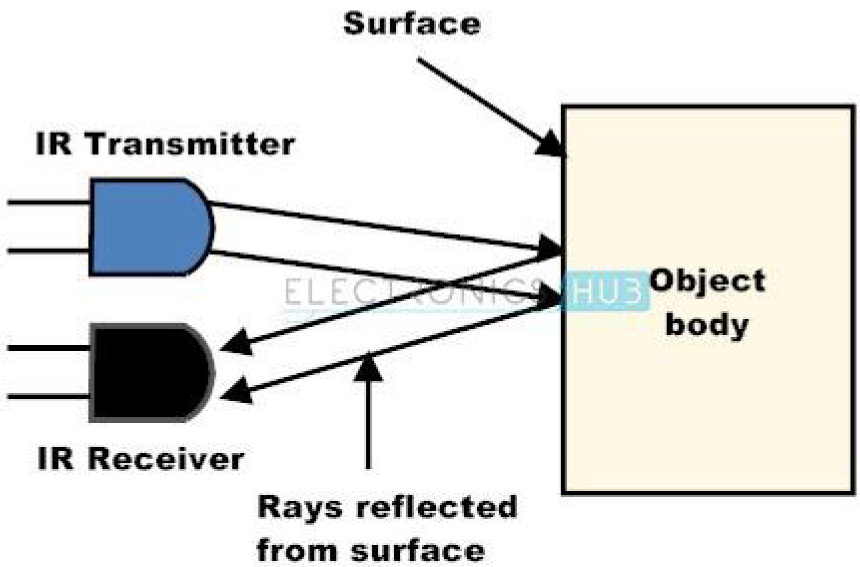


Figure 6: Infrared Sensor https://www.electronicshub.org/ir-sensor/

LiDAR is a range-finding environmental sensor that uses lasers for adaptive cruise control, collision avoidance, and object recognition. LiDAR has improved spatial resolution and range accuracy compared to MMWR. LiDAR is frequently used in ground devices post-crash for accident reconstruction. However, vehicular LiDAR scanners have yet to be utilized for a crash investigation. LiDAR is limited by foggy or extreme weather conditions; it works best with good lighting but can also operate well at night.

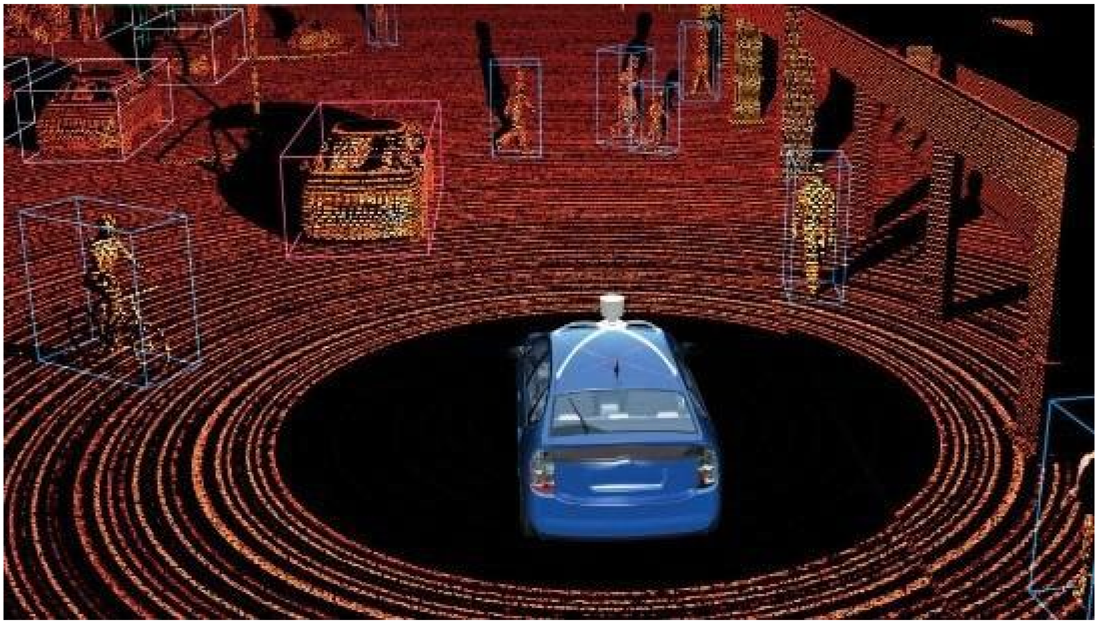


Figure 7: LiDAR https://news.voyage.auto/an-introduction-to-lidar-the-key-self-driving-car-sensor-a7e405590cff

AVs use cameras for lane detection, landscape detection, object detection, object tracking, and video-based navigation. Aftermarket dashboard cameras are already commonly used in crash investigations; however, camera footage obtained from AV sensors can also be beneficial to reconstruct crash events. The images below depict footage obtained from a Tesla vehicle that was not involved in the crash but was on-scene as a witness. This footage directly conflicted with the statement given to the police by the driver involved, who claimed he was swerving to avoid a speeding car behind him

Figures 8-11: Crash Events Recorded by an AV Camera Sensor. The top left image was captured from the back passenger's side camera, whereas the other three are from the front camera. As shown, the white car in the top left sped past the Tesla vehicle, then caused the crash shown in the bottom left, and finally rested as shown in the bottom right picture.

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Fogue, M., Garrido, P., Martinez, F. J., Cano, J.-C., Calafate, C. T., Manzoni, P., & Sanchez, M. (2011). Prototyping an automatic notification scheme for traffic accidents in vehicular networks. 2011 IFIP Wireless Days (WD), 1–5. https://doi.org/10.1109/WD.2011.6098139

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1. How many sworn officers work in your organization?

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2. Does your organization have a separate division charged with investigating crashes?

○ Yes (1)

○ No (2)

○ Other (3) ____

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3. What is your role in collision investigation? Select all that apply.

☐ Patrol (1)

☐ Traffic Division (2)

☐ Crash Reconstructionist (3)

☐ Other (4) ____

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4. How many fatal and/or prosecutable crashes have you worked on?

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End of Block: Orientation

Start of Block: Work Experience

5. Has your organization provided the opportunity for training on the use of automated vehicle sensor data for crash reconstruction purposes?

- ○ Yes (1)
- ○ No, but we have a specific plan to implement this training (4)
- ○ No, but we expect to have a specific plan to implement this training in the future (3)
- ○ No, and we do not plan to implement this training (2)
- ○ N/A or unsure (6)

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6. Does your organization have access to the processing or managing of crash data from vehicles involved in a collision?

- ○ Yes (1)
- ○ No, but we have a specific plan for this (2)
- ○ No, but we expect to have a specific plan for this in the future (3)
- ○ No, and we don't plan for this (4)
- ○ N/A or unsure (5)

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7. Have you ever used vehicle camera footage during a crash investigation? If so, how did this footage impact the process and outcome of the investigation?

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8. Have you ever used in-vehicle LiDAR equipment during a crash investigation? If so, how did this in-vehicle LiDAR data impact the process and outcome of the investigation?

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9. Have you ever used in-vehicle radar sensors during a crash investigation? If so, how did the use of in-vehicle radar impact the process and outcome of the investigation?

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10. What software or other tools do you typically use during a crash investigation (e.g., Analysis and Simulation Software, Total Stations, Drone Cameras, Event Data Recorders)?

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11. Have you ever used Event Data Recorders (EDRs) for collision investigation?

○ Yes (1)

○ No (2)

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12. What information have you typically received from the EDR automatically after a collision? (Select all that apply)

- ☐ Vehicle speed (1)
- ☐ Engine RPM (2)
- ☐ Brake status (3)
- ☐ Throttle position (4)
- ☐ Seatbelt usage (5)
- ☐ Steering input (7)
- ☐ Other (6) ________________________________

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13. Have you completed any training for EDR data retrieval? If so, please specify which course(s) you have completed.

- ☐ EDR Technician (4)
- ☐ EDR Basic (5)
- ☐ EDR Advanced (6)
- ☐ Other (7) ________________________________

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14. Have you completed any training for automated vehicle data retrieval? If so, please specify which course(s) you have completed.

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15. Does the current process of collision investigation adequately fulfill each of the following aspects of collision investigation? Rank adequacy using the provided scale points.

	Very inadequate (1)	Inadequate (2)	Somewhat adequate (3)	Adequate (4)	Excellent (5)
Accuracy and reliability of collision investigations (1)	○	○	○	○	○
Improvement of safety and mitigation of future collision investigations (2)	○	○	○	○	○
Efficiency and speed of collision investigations (3)	○	○	○	○	○
Data availability during collision investigations (4)	○	○	○	○	○
Standardization of how collisions are investigated (5)	○	○	○	○	○
Training and certification for collision investigation (6)	○	○	○	○	○

16. Is there anything else that could be improved about the current process of collision investigation?

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17. Thinking of the future of collision investigation, what information (not usually available today) would you most like to get from a vehicle automatically after a collision?

- ○ Vehicle and occupant dynamics (1)
- ○ Environmental data (2)
- ○ Vehicle systems and performance (3)
- ○ Other (4) ____

18. Of the available data sources in automated vehicles mentioned, which would provide the most helpful information that is not currently available? (Select all that apply.)

- ☐ Global Positioning System (GPS) (1)
- ☐ Onboard Units (OBU) (2)
- ☐ Millimeter Wave Radar (MMWR) (3)
- ☐ Ultrasound (4)
- ☐ Infrared (5)
- ☐ LiDAR from vehicles (6)
- ☐ Cameras (7)
- ☐ Other (8) ____

19. What are some significant barriers based on your work experience for using automated vehicle sensor data in crash reconstruction? (Select all that apply.)

- [ ] Data availability and accessibility (1)
- [ ] Data format and standardization (2)
- [ ] Data analysis (3)
- [ ] Liability and privacy concerns (4)
- [ ] Technical complexity (5)
- [ ] Budget (7)
- [ ] Time (8)
- [ ] Other (6) ____

20. Based on your work experience, how can automated vehicle sensor data enhance crash investigation? (Select all that apply.)

- ☐ Increased data availability (1)
- ☐ Improved data accuracy (2)
- ☐ Enhanced vehicle and occupant safety (3)
- ☐ Improved understanding of human factors (4)
- ☐ Improved understanding of environmental factors (5)
- ☐ Other (6)

21. Please rate your familiarity with the following automated vehicle technologies using the provided scale points.

	Not at all familiar (1)	Slightly familiar (2)	Somewhat familiar (3)	Moderately familiar (4)	Extremely familiar (5)
Global Positioning System (GPS) (1)	○	○	○	○	○
Onboard Units (OBU) (2)	○	○	○	○	○
Millimeter Wave Radar (3)	○	○	○	○	○
Ultrasound (4)	○	○	○	○	○
Infrared (5)	○	○	○	○	○
LiDAR (6)	○	○	○	○	○
Cameras (7)	○	○	○	○	○

22. Please rate your familiarity with the following advanced driver-assistance system technologies using the provided scale points.

	Not at all familiar (1)	Slightly familiar (2)	Somewhat familiar (3)	Moderately familiar (4)	Extremely familiar (5)
Adaptive Cruise Control (ACC) (1)	○	○	○	○	○
Lane Departure Warning (LDW) (2)	○	○	○	○	○
Blind Spot Monitoring (BSM) (3)	○	○	○	○	○
Rear Cross Traffic Alert (RCTA) (4)	○	○	○	○	○
Forward Collision Warning (FCW) (5)	○	○	○	○	○
Automatic Emergency Braking (AEB) (6)	○	○	○	○	○
Park Assist (7)	○	○	○	○	○
Night Vision (8)	○	○	○	○	○
Head-Up Display (9)	○	○	○	○	○

	Not at all familiar (1)	Slightly familiar (2)	Somewhat familiar (3)	Moderately familiar (4)	Extremely familiar (5)
Driver Monitoring Systems (DMS) (10)	○	○	○	○	○

23. Please rate your familiarity with the following law enforcement training topics using the provided scale points.

	Not at all familiar (1)	Slightly familiar (2)	Somewhat familiar (3)	Moderately familiar (4)	Extremely familiar (5)
Understanding automated vehicle technology: This includes training on how CAVs work, the different sensors and systems used to drive the vehicle, and the communication protocols used by AVs to interact with other vehicles and infrastructure. (1)	○	○	○	○	○
Legal and ethical considerations: Law enforcement personnel need to be aware of the legal and ethical implications of CAVs, including privacy, security, and liability issues. (2)	○	○	○	○	○

	Not at all familiar (1)	Slightly familiar (2)	Somewhat familiar (3)	Moderately familiar (4)	Extremely familiar (5)
Traffic enforcement and regulation: With the increasing use of CAVs, law enforcement personnel must be trained in how to enforce traffic regulations and respond to incidents involving CAVs. (3)	○	○	○	○	○
Incident response and crash investigation: Law enforcement personnel will need to be trained on how to respond to and investigate incidents involving CAVs, including collecting and preserving evidence and interacting with CAV manufacturers during an investigation. (4)	○	○	○	○	○

	Not at all familiar (1)	Slightly familiar (2)	Somewhat familiar (3)	Moderately familiar (4)	Extremely familiar (5)
Cybersecurity: As CAVs rely on complex systems and networks, law enforcement personnel need to be trained on the various cybersecurity risks and threats to CAVs, and how to respond to cyber-attacks. (5)	○	○	○	○	○
Human factors: Law enforcement personnel need to understand the impact that CAVs may have on human behavior, such as changes in driver behavior, and how to address related safety concerns. (6)	○	○	○	○	○

	Not at all familiar (1)	Slightly familiar (2)	Somewhat familiar (3)	Moderately familiar (4)	Extremely familiar (5)
Communication and community engagement: Law enforcement personnel need to be trained on how to communicate and engage with communities about the benefits and risks associated with CAVs, and how to address public concerns and misconceptions about the technology. (7)	o	o	o	o	o

24. Do you have any final thoughts regarding crash investigation, automated vehicle or advanced driver-assistance system technology, or other related topics?

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End of Block: Work Experience