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Automated vehicle data pipeline for accident reconstruction: New insights from LiDAR, camera, and radar data

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ABSTRACT

As automated vehicles are deployed across the world, it has become critically important to understand how these vehicles interact with each other, as well as with other conventional vehicles on the road. One such method to achieve a deeper understanding of the safety implications for Automated Vehicles (AVs) is to analyze instances where AVs were involved in crashes. Unfortunately, this poses a steep challenge to crash-scene investigators. It is virtually impossible to fully understand the factors that contributed to an AV involved crash without taking into account the vehicle's perception and decision making. Furthermore, there is a tremendous amount of data that could provide insight into these crashes that is currently unused, as it also requires a deep understanding of the sensors and data management of the vehicle. To alleviate these problems, we propose a data pipeline that takes raw data from all on-board AV sensors such as LiDAR, radar, cameras, IMU's, and GPS's. We process this data into visual results that can be analyzed by crash scene investigators with no underlying knowledge of the vehicle's perception system. To demonstrate the utility of this pipeline, we first analyze the latest information on AV crashes that have occurred in California and then select two crash scenarios that are analyzed in-depth using high-fidelity synthetic data generated from the automated vehicle simulator CARLA. The data visualization procedure is demonstrated on the real-world Kitti dataset by using the YOLO object detector and a monocular depth estimator called AdaBins. Depth from LIDAR is used as ground truth to calibrate and assess the effect of noise and errors in depth estimation. The visualization and data analysis from these scenarios clearly demonstrate the vast improvement in crash investigations that can be obtained from utilizing state-of-the-art sensing and perception systems used on AVs.

1. Introduction

According to the National Highway Traffic Safety Administration (NHTSA), more than 6 million vehicle crashes are reported across the United States each year, leading to around 2 million injuries and 37,000 fatalities (Federal Highway Administration (FHWA), "Highway Statistics, 2016). As automated vehicles diffuse through the transportation system, they are expected to improve safety. However, when they do crash, often with conventional vehicles, bicycles, scooters, or pedestrians, they curate a vast amount of data originally intended for sustained sensing of the surrounding environment. These data have the potential to be used for detailed crash scene analysis, provided an event-dependent workflow, including sensor selection, processing, analysis, and visualization is standardized and made available to law enforcement. This study provides an overview of AV-involved crashes and leverages data from carefully selected AV-involved crashes that come from the California Autonomous Vehicle Tester Program. The crashes are simulated with the objective of obtaining sensor information and showing how the data can be analyzed.

More broadly, the analysis of AV-involved crash data from this program, initiated in 2014, shows that the frequency and causes of certain types of AV-involved crashes are different, with human-driven vehicles more likely to rear-end AVs. This points to the need to investigate in detail the causes of AV-involved crashes while harnessing detailed data available from connected and autonomous vehicles (CAV's) (Boggs et al., 2019). Specifically, radar, cameras, and LiDAR sensors utilized by Automated Driving Systems or ADS (e.g., automatic emergency braking, adaptive cruise control, lane keeping assist), Basic Safety Messages used in V2X communications (e.g., vehicle position, speed, heading, acceleration) and driver monitoring provide new

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detailed data to identify contributing factors in crash investigations, such as driver/operator state, vehicle automation levels, locations of objects and people in the vicinity of the scene, vehicle performance and diagnostic data, and environmental factors. Moreover, recent high-profile crashes involving automated vehicles, especially vehicles being used and tested by Tesla and Uber indicate that crash investigators can greatly benefit from data access and more accurate contributing factor identification (e.g., driver distraction) through sensor data (National Transportation Safety Board (NTSB), "Collision Between a Car Operating With Automated Vehicle Control Systems and a Tractor-Semitrailer Truck Near Williston, Florida, May 7, 2016; National Transportation Safety Board (NTSB), "Preliminary Report: HWY18FH011,", 2018; Board, 2018; National Transportation Safety Board (NTSB), "Preliminary Report: HWY19FH008,", 2018). Currently, this needs to be done in cooperation with the manufacturer, which introduces additional delays in an already complex investigation process. This paper also highlights the need for a standardized workflow, including sensor selection, processing, analysis, and visualization which are all event dependent. The end goal is to develop a semi-automated tool for accident reconstruction for law enforcement.

In this research, the main objective is to use the safe system approach to harness data generated by AV sensors, extract features from the data, and incorporate such information into crash investigation analysis. To illustrate the developed methodology, we first analyze the latest information on AV crashes that have occurred in California and select two separate sample AV-involved crashes in California. They are then simulated in the CARLA software. The paper discusses how AV sensors including LIDAR, camera, and radar can be utilized to investigate pre-crash driver states, crash involved movements (e.g., vehicles, pedestrian, bike), and the surrounding environment. This is demonstrated on a sequence of frames from the real-world Kitti dataset by tracking a leading vehicle from the instrumented vehicle using YOLO object detection and a monocular depth estimator called AdaBins. Depth from LIDAR is used as ground truth to calibrate and assess the effect of noise and errors in depth estimation using cameras. A main take-away from this study is that the end outcome (a rear-end collision, for example) is often coupled to the functioning of the automated vehicle subsystems through complex dependencies, even though a casual glance might find the following vehicle to be at fault due to failure to stop.

2. Background

2.1. Literature on crash investigations

The literature has widely discussed the association of factors contributing to crashes and has shown that human error contributes to more than 90 % of crashes. However, in the majority of such crashes, more than one factor contributes to crash occurrence. Generally, human errors and failures are considered the main factor, ignoring other reasons and interactions of different factors, especially the surrounding environment and vehicle characteristics. Several studies attempted to perform crash investigations using police report data (Haghighi et al., 2018; Shinstine et al., 2016; Hezaveh et al., 2019).The main limitation with police reported crash datasets is that they usually only record one contributing factor. Furthermore, such information is recorded after the crash occurrence, mainly based on the police officer's observations and judgment, which might not fully reflect the pre-crash circumstances and the complexity of the event. To mitigate this issue, some studies utilized different data sources to incorporate information on vehicular movements and the surrounding environment. For instance, Wali et. al. attempted to utilize unstructured crash narrative data to analyze injury severity of rail-trespassing crashes involving pedestrians and bicyclists (Wali and Khattak, 2020).

Event Data Recorders (EDRs) are one of the most important data sources, and they are estimated to be in most of new vehicles with procedures for accessing and analyzing the data. Much information can be retrieved from an EDR including time, speed, changes in speed (ΔV), throttle and brake position, seatbelt, and airbag status. Several studies utilized EDR to integrate pre-crash vehicular movements in their analysis (Scanlon et al., 2015; Kusano and Gabler, 2013; Kononen et al., 2011; Augenstein, et al., 2007; Scanlon et al., 2015). For example, Scanlon et al. studied the drivers' pre-crash maneuvers in terms of timing and kinematics using 5 s of vehicle speed, brake, and yaw rate data before crashes. Other studies have used Principal Direction of Force (PDOF) recorded by the EDR as a surrogate measure to estimate the damage side of crashes. Furthermore, the EDR data has been used in crash injury prediction.

Police reported crash datasets suffer from unreported crashes and lack of detailed information on driver condition, vehicular movements, and surrounding environment. It is worth noting that around 50 % of no-injury collisions and 25 % of minor-injury collisions are not reported to the police (National Highway Traffic Safety Administration (NHTSA), "Traffic safety facts: Motorcycles,", 2009). Naturalistic driving studies (NDS) attempted to overcome the limitations of police report datasets by collecting data on driver, vehicle, and surrounding environment. Several studies that investigated crashes using such factors shed more light on pre-crash factors contributing to a crash occurrence (Arvin et al., 2019; Kamrani et al., 2019; Dingus, et al., 2016).They have shown that incorporating additional collected information through instrumented sensors on vehicles (i.e. camera, accelerometers, and forward sensors) can substantially improve crash investigations.

2.2. Literature on using AV sensors

One limitation of EDR devices is that they only collect data from the subject vehicle, ignoring the surrounding vehicles, environment, and driver behaviour. Furthermore, EDR does not account for emerging advanced driver assistance systems (ADAS), which allow a driver to dynamically transfer vehicle control responsibilities to a driving assistant system for prolonged periods. As low-level automated vehicles gradually penetrate the market, new data sources generated by such vehicles enable researchers to perform novel analysis. As an illustration, the National Transportation Safety Board has investigated three fatal AV-involved crashes in the US (National Transportation Safety Board (NTSB), "Collision Between a Car Operating With Automated Vehicle Control Systems and a Tractor-Semitrailer Truck Near Williston, Florida, May 7, 2016). These data sources enabled investigators to obtain pre-crash information on driver, vehicle, and surrounding environment characteristics. For example, analysis on the Tesla Model S crash in Florida lead to the extraction of 53 specific variables covering various system error messages from up to 42 h before the crash (National Transportation Safety Board (NTSB), "Collision Between a Car Operating With Automated Vehicle Control Systems and a Tractor-Semitrailer Truck Near Williston, Florida, May 7, 2016). Using such data, they were able to determine the times and locations where autopilot systems were used, instances where warnings were generated to the driver, and the times where the driver interacted with the steering wheel prior to the crash (Fig. 1).

With the recent influx of vehicles on the roads with some form of autonomous driving capability, many research questions are being raised which are specific to these vehicles in the context of accident analysis. Namely, there is interest in uncovering what types of accidents are occurring which may be specific to AVs, and how the additional sensor data be used to further supplement these analyses. Zhu et. al. analysed limited AV collision severity data to determine that vehicle manufacturer and vehicle maneuver at the time of accident were highly correlated with crash severity, while Wang et. al. were able to pinpoint perception tracking issues associated with LiDAR and Radar data as the cause for many reported disengagements of the AV's self-driving functionality (Zhu and Meng, 2022/09/01/ 2022,; Wang and Li, 2019). Sensor data can also be used to analyse accidents and perform accident prevention on a case-by-case basis. Kikuchi et. al. demonstrate the

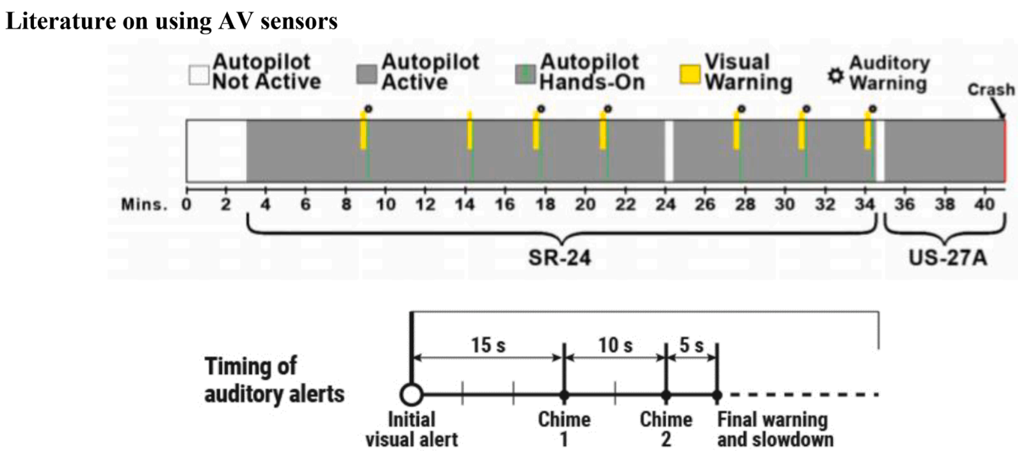


Fig. 1. Illustration of pre-crash autopilot state and warnings to the driver of Tesla fatal crash (NTSB, 2016).

conditions from which sonar can replace rear-view cameras as an effective means to prevent collisions with pedestrians, while Yu et. al. show how vehicle kinematics gleaned from advanced sensing can be used to provide additional insight in accident analysis (Kikuchi et al., 2021/03/01/ 2021,; Yu and Li, 2022/03/01/ 2022). The recent research that highlights the utility of advanced sensor data in accident analysis justifies the work done in this research to organize, visualize, and explain how this sensor data could be collected and distributed to interested parties.

AV instrumentation with a wide range of sensors help us collect unique data and incorporate it into the current state of the art. Focusing on safety analysis, a few studies have used roadside and vehicle LiDAR data to process vehicular safe movements and the environment (Lindner and Wanielik, 2009), track pedestrians and vehicles (Zhao et al., 2019), identify occurrence of a crash and near-crash events (Wu et al., 2018; Wu et al., 2020), and predict crash parameters (Sequeira et al., 2019). By reviewing the literature, we can infer that there is a lack of framework to integrate data generated by LiDAR, camera, and radar into the crash investigation analysis. This study attempts to address this gap by developing a unique framework to integrate AVs senor data and use them in crash investigation analysis and also to correlate the accident with specific AV system failures or shortcomings that often may be compounded with human errors.

2.3. Study design

This study introduces a framework for leveraging newly available AV data collected by multiple sensors to understand AV-involved crashes and extract useful information from such data to incorporate it in the safety analysis. This study takes advantage of data provided in AV-involved crashes in the California tester program. We first analyze the latest information on AV crashes that have occurred in California and then simulate two sample crashes in the CARLA simulation software to demonstrate the advantages and challenges of using AV sensors in crash investigation. Furthermore, the sensitivity of analysis on sensor resolution and data degradation due to weather conditions is studied.

2.4. Framework

The framework of the study is provided in Fig. 2. The safe system framework integrates data generated from different sensors, which monitors the AV, driver, roadway, and environment. Data integration generated by AV sensors provides a full picture of crashes and helps us perform detailed crash investigations. These data parameters can help us

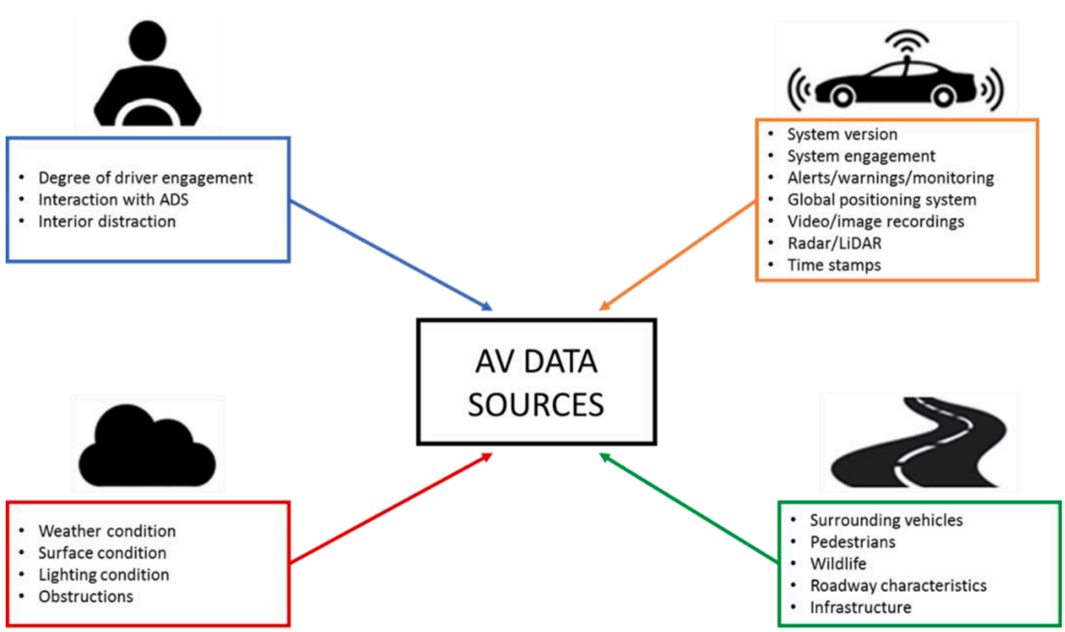


Fig. 2. Framework to incorporate AV data into crash investigation analysis.

understand the performance of automated driving systems involved in a crash and the control actions taken by the ADS and the driver as well as the situation before and during the crash.

2.5. California tester program

The Department of Motor Vehicles in California facilitated AV manufacturers testing automated systems in the transportation network by establishing the Autonomous Vehicle Tester Program in 2014 (State of California Department of Motor Vehicles). The two primary requirements of the program are that manufacturers report all AV-involved crashes through a standardized form and fully retain all ADS disengagement details. The testing includes vehicles that can be considered as Level 2 and 3 automation, where the driver is meant to take over manual control in complex and dangerous situations. For this study, we utilized an AV-involved crash for which the standard form was available, which provided information on the damage location and severity of the AV, weather, lighting, roadway surface, pre-crash vehicle movements, and other associated factors.

2.6. Real world scenarios

The data in this study are deemed to be of high quality, as they come from real-world crashes where basic facts were reported by the CA DMV. Under the proposed plan, the data will have come from deployed sensors and are likely to be valid.

2.7. Key statistics

Based on crash records from 148 AV collision reports in California reported by the Report of Traffic Collision Involving an Autonomous Vehicle (OL316 form), the key statistics are summarized in TABLE 1. It should be noted that they are reported by AV manufacturers. In 94 cases (63.5 %), the AVs were operating in the autonomous driving mode before getting in a crash. In the remaining 54 cases (36.5 %), the AVs were in the conventional mode before getting a crash. We reviewed the key statistics as follows focusing on those cases where the AVs were operating in the autonomous driving mode.

Notably, 34.0 percent of the AVs in the autonomous driving mode were manually disengaged by their drivers to the conventional mode. Regarding manner of collision, 70.2 percent of the crashes had a rear-end collision, emerging as the dominant manner of collisions, while 16.0 percent had a sideswipe collision. About 7.5 % of the crashes involved a pedestrian or bicyclist, i.e., vulnerable road users. Concerning vehicle manufacturers, 60.6 percent of the crashes involved the AVs manufactured by Cruise LLC, while 26.6 percent involved the AVs manufactured by Waymo LLC and 8.5 percent involved the AVs manufactured by Zoox, Inc.

Moreover, the statistics show the information on the weather and lighting condition where the AV-involved crashed occurred. When it comes to the weather condition, 91.5 percent of the crashes occurred in clear weather (notably, the Bay Area is known for good weather), while the remaining ones occurred in cloudy, rainy, or foggy weather. With regard to the lighting condition, 67.0 percent of the crashes occurred in daylight, while 27.7 percent occurred in darkness with streetlights.

Furthermore, the statistics provide information on the vehicle movements right before a crash occurred. It is revealed that 22.3 percent of the crashes occurred when an AV was stopped while the second vehicle was proceeding straight. In addition, 17.0 percent of the crashes occurred when both an AV and the second vehicle were proceeding straight. Besides, we can see the information on the damage level of AVs and injuries reported by AV manufacturers. When it comes to the AV damage level, 85 AVs (90.4 %) were damaged, 68 of which (72.3 %) had a minor damage while 15 AVs (16.0 %) had a moderate damage, and 2 AVs (2.1 %) had a major damage. Meanwhile, 24.5 percent of the crashes caused injury to at least one person.

Table 1
Key Statistics of AV Crashes in California from 2019 to 2020 (N = 148).

Variable	Autonomous Mode (N = 94)		Conventional Mode (N = 54)	
	Frequency	%	Frequency	%
Vehicle Manufacturer				
Cruise LLC	57	60.6	19	35.2
Waymo LLC	25	26.6	11	20.4
Zoox, Inc.	8	8.5	13	24.1
Other	4	4.3	11	20.4
Manual Disengagement	32	34.0	NA	NA
Weather Condition				
Clear	86	91.5	50	92.6
Cloudy	6	6.4	3	5.6
Raining	1	1.1	1	1.9
Foggy	1	1.1	0	0.0
Lighting Condition				
Daylight	63	67.0	48	88.9
Dusk/Dawn	4	4.3	0	0.0
Dark with Street Lights	26	27.7	6	11.1
Dark without Street Lights	1	1.1	0	0.0
Vehicle Movements (AV, 2nd Vehicle)				
(Stopped, Straight)	21	22.3	12	22.2
(Slowing/Stopping, Straight)	5	5.3	1	1.9
(Straight, Straight)	16	17.0	2	3.7
(Straight, Changing Lanes)	10	10.6	4	7.4
(Left, Straight)	1	1.1	2	3.7
Other	41	43.6	33	61.1
Involving Pedestrian or Bicyclist	7	7.5	4	7.4
Manner of Collision				
Rear-End	66	70.2	23	42.6
Sideswipe	15	16.0	13	24.1
Broadside	9	9.6	3	5.6
Head-On	1	1.1	8	14.8
Other	3	3.2	7	13.0
AV Damage Level				
None	9	9.6	6	11.1
Minor	68	72.3	39	72.2
Moderate	15	16.0	9	16.7
Major	2	2.1	0	0.0
Injury to at least one person	23	24.5	8	14.8

After reviewing the descriptive statistics from these 148 crashes from January 2019 to December 2020, we selected two AV-involved crashes. These crashes were chosen based on several criteria. First, as the most dominant AV-involved crash type, a rear-end conflict between AVs and conventional vehicles was selected. Second, the interaction between AVs and pedestrians is one of the key AV challenges, which can be studied in this context. Finally, a typical roadway environment is selected for simulation purposes. Detailed information regarding the selected two collisions is provided in TABLE 2.

The narratives of these two crashes, available in the reports, are as follows:

Crash #1 narrative: "A Cruise autonomous vehicle ("Cruise AV"),

Table 2
Information on selected AV-involved crashes.

Variable	Description of Crash #1	Description of Crash #2
Date of accident	08/07/2019	11/29/2019
Time	10:23 AM	10:41
Location	24th between NOE and Sanchez St. San Francisco, CA	Embarcadero St. and Washington St.
AV operation mode	Autonomous	Autonomous; Disengaged just before the crash
AV Movement prior to the crash	Stopped	Moving- Slowing
Conventional vehicle movement	Moving-Entering traffic	Moving- Going straight
Collision type	Rear end	Rear end
Weather condition	Clear	Clear
Lighting	Daylight	Daylight
Roadway condition	No unusual conditions	No unusual conditions

operating in autonomous mode, was traveling eastbound on 24th Street between NOE and Sanchez Streets when the Cruise AV yielded to a pedestrian crossing the roadway midblock outside of a crosswalk and for clearance to maneuver around a double-parked vehicle immediately ahead of it. While the Cruise AV waited, another vehicle pulling out of a driveway and into the Cruise AV's lane and made contact with the left rear corner of the Cruise AV, damaging the Cruise AV's left rear bumper, fender, and radar. There were no injuries and police were not called.".

Crash narrative: "A Cruise autonomous vehicle ("Cruise AV"), operating in autonomous mode, was traveling southeast bound on The Embarcadero at the intersection with Washington Street when the Cruise AV slowed down. The driver of the Cruise AV disengaged from autonomous mode and, shortly thereafter, another vehicle made contact with the rear bumper of the Cruise AV, damaging the Cruise AV's rear fascia assembly and radars. There were no injuries reported at the scene by either party and police were not called. Both of the Cruise AV test operators later mentioned neck and back pain.".

The approximate locations of each accident are shown from Google Street View in Fig. 3. Using these descriptions as representatives of accidents involving AV's, we intend to show in the remainder of this paper the value of AV sensors in crash analysis by recreating a combination of these two accidents inside a driving simulation.

3. Methodology

3.1. Complete data pipeline

This study introduces a framework to collect, organize, and analyze data from sensors that are commonly found on modern developmental autonomous vehicles. Under normal operation, these sensors are used to localize the AV and detect relevant objects around the vehicle in order to plan motion. This data is typically of much higher quality than what may be found in the EDR on conventional vehicles. As such, this data can be used for crash reconstruction and analysis that is of much higher fidelity than what can be obtained from basic vehicle information or witness testimony. As shown in Fig. 4, we propose a complete data pipeline that takes raw sensor data from the vehicle and automatically processes the data for visualization and analysis.

3.2. Data processing

Given a stream of high-quality data from the sensors listed in the above section, this data must be sorted and processed to give results that can be visualized and are actionable. For visualization and analysis, we will focus on the three most common data modalities used by CAVs for the purpose of high-fidelity crash reconstruction:

1) A Lidar 3D point cloud scan of the surrounding environment collected across time.
2) Video from all available cameras leading up to and during the crash.
3) Position and velocity of the AV, other vehicles in the scene, and other relevant factors such as bicyclists or pedestrians. All data are collected across time.

3D Point Cloud: 3D point cloud data is collected directly from LiDAR and radar sensors. LiDAR systems collect hundreds of thousands of data points every second - so in order to deal with memory constraints, a preprocessing step is common for down sampling the data. For visualization and analysis, the data from the radar and LiDAR systems will need to be converted to the same cartesian coordinate system. Since the LiDAR unit is typically located centrally on the vehicle, the inherent coordinate frame of the lidar sensor will become the coordinate frame for all other forms of data in the pipeline. Radar data can be transformed into the LiDAR coordinate frame as:

$$X_r^{'} = X_r L_{rotation} + L_{translation}$$

where X_r s any raw data radar vector, $L_{rotation}$ s the rotation transformation from the radar coordinate frame to the LiDAR coordinate frame, and $L_{translation}$ s the 3D distance between the sensors. Once this transformation is complete, radar data and lidar data can be combined into one data structure representing the 3D point cloud of the environment surrounding the crash. Finally, timestamps from both sensors allow the data to be synchronized leading up to the crash.*Scene Video:* Scene video can be captured directly from any camera sensors on-board the AV. This video is natively timestamped for synchronization with data captured from other videos, as well as the point cloud data.

Object Position/Velocity: Velocity data for the AV are supplied directly from the IMU's inside the vehicle. While virtually all AV's will have access to GPS data as well for global positioning, "dead reckoning" techniques can also be combined with LiDAR information to track vehicle position (Akai, et al., 2017). Detecting the position of other actors in the scene such as third-party vehicles, pedestrians, or bicyclists first requires object detection and identification, either through pixel level segmentation or by locating the corners of a bounding box around the object of interest. Given access to a dense 3D point cloud and 2D images, there are many algorithms for effectively identifying and locating relevant objects in the scene. Some state-of-the-art algorithms produce 3D bounding boxes around objects directly from point cloud data (Zhou and Tuzel, 2018; Shi et al., 2019). Others use sensor fusion techniques to combine 2D object detection from camera images with 3D

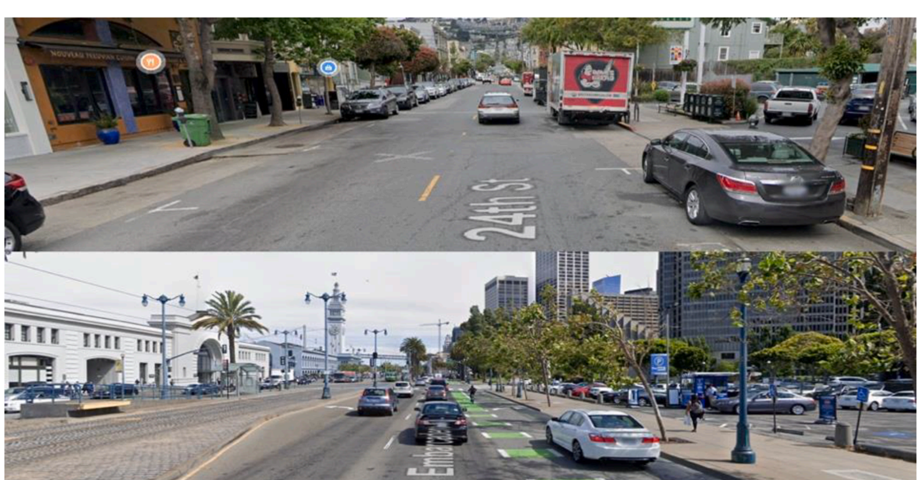


Fig. 3. Crash #1 (Top), Crash #2 (Bottom). Both Images taken from Google Street View in approximate locations described in their respective police narratives.

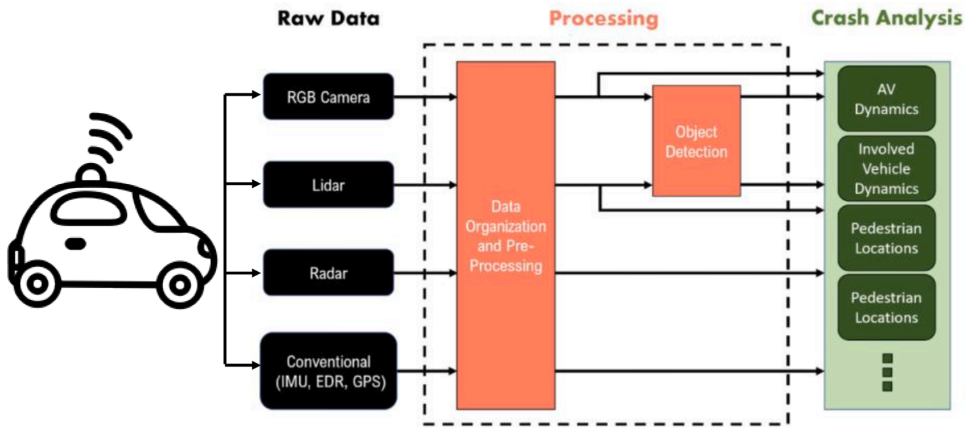


Fig. 4. The proposed data pipeline. Raw data collection and processing take place in a "black box", effectively removing the need for underlying knowledge of vehicle sensors to analyze driving behavior & crash reconstructions.

point cloud data (Qi et al., 2018; Ku et al., 2018). An illustration of this entire procedure is outlined in the following section, where a YOLO based object detector followed by a monocular depth estimator called *AdaBins* are applied on scenes from the real-world Kitti dataset.

Regardless of the detection algorithm used, the result will be the 3D position of all relevant actors in the scene. The velocity of any actor can be calculated with the discrete time derivative of position:

$$v_n(x,t) = \frac{x_n - x_{n-1}}{t_n - t_{n-1}} + v_{AV}$$

where x_n nd t_n epresent the current location and time of the object detection, x_{n-1} nd t_{n-1} epresent the last known location and time of detection, and v_{AV} epresents the speed of the vehicle on which the LiDAR is attached, calculated, or read directly from the vehicle IMU. Finally, to make use of all of these sensors, they must be synchronized across time. This is a common problem in mobile robotics, including self-driving vehicles. There are many solutions in literature, and thus is not addressed in this research (Fridman et al., 2016; Olson, 2010).

3.3. Data visualization procedure on real data

The purpose of the procedure outlined in this section is to add clarity to the process of scene reconstruction from RGB images and LIDAR point clouds utilizing the sensor data collected on-board AVs during accidents. We validate this procedure on a high-quality real-world dataset. We also demonstrate how the position of a leading vehicle can be accurately determined using images and point cloud data, in addition to simply highlighting the utility of visualizing raw data and the output of our image processing models directly. This will shed light on how the visualizations performed on simulated data in the remainder of this research could be produced on real data.

Kitti Dataset: The dataset used for real world validation of our data processing procedure was the Kitti dataset (Geiger et al., 2013/09/01/ 2013). The Kitti dataset has 7,481 training images across three scenes in Karlsruhe, Germany, and was created with the purpose of aiding research in the field of autonomous vehicles. GPS, images from two front-facing cameras, and 360-degree scans from a 64 laser Velodyne LiDAR are recorded for every timestamp. All data instances are also paired with labels that indicate what can be found in the data - namely, six classes of objects: [*car, cyclist, pedestrian, tram, truck, van]*. These labels also indicate where these objects can be found in the images using 2D bounding boxes. These bounding boxes take the form of a 4-dimensional value for every object: $(X_c, Y_c,\ w,\ h,\ c)$ where X_c nd Y_c epresent the center point of the object in pixels while w and h are the width and the height of the object, also measured in pixels. The class of the object is denoted by c.

Image processing model (YOLO): In instances where simply visualizing the raw sensor data may not provide enough information, additional data processing tools are needed. You Only Look Once (YOLO) is a mature object detection algorithm that passes images through a convolutional neural network (CNN) and attempts to correctly predict the labels of the image, as provided by the Kitti dataset (Redmon et al., 2016). Specifically, we used the Ultralytics YOLOv5 architecture to perform our proof of concept (ultralytics, yolov5, , 2022). The output of the model is in the same format as the labels in the dataset, with an additional *confidence* value: $(x_c, y_c,\ w,\ h,\ c,\ conf)$ This *conf* value represents the likelihood that the object at that location is really there and accurately detected, and falls in the range of [0,1]. The user sets a *confidence threshold,* below which all detections are ignored. The confidence threshold of our model was set at 0.4.

Case 1: **Tracking with LIDAR and camera:** As shown in Fig. 5, in this workflow, object detection with YOLO is accompanied by projecting the LIDAR point cloud onto the image plane. The procedure for projecting LiDAR points onto the image are provided in (Geiger et al., 2013/ 09/01/ 2013). Once this projection is done, LiDAR points and camera images are in the same coordinate system, where each LiDAR point contains a 2D pixel location $x_L, y_L()$and a depth measurement $d_L()$n meters. The LIDAR depth measurements $d_L()$re now interpolated to provide $\left(d_L\ (x_c, y_c)\ \right)$ which serves as an accurate estimate of the object distance for tracking. It may be noted that LiDAR and camera images are not fused within the YOLO model. Instead, the YOLO model provides x_c, $y_c()$hile LiDAR provides the depth estimates.

This procedure can be repeated for any sensor modality that produces point cloud data. While the KITTI dataset only contains point cloud data in the form of LiDAR, many vehicles are equipped with radar sensors. Since radar is also in the form of 3D point cloud data, the procedure is identical to LiDAR.

Case 2: **Tracking with only camera:** In the absence of a LIDAR, we need an alternate way of estimating distance to objects of interest. For this application, we used a monocular depth estimation model that provides a depth estimation for every pixel in an image using CNNs. For our purposes, we chose to use the monocular depth estimator AdaBins (Bhat et al., 2021). This model was chosen due to the fact that a pretrained model for the Kitti dataset is readily available, making integration into a workflow seamless, as well as the fact that it currently ranks highly on the Kitti depth estimation leader board (xxxx). Both the YOLO model and the AdaBins model were trained using the entire Kitti dataset. At this stage, finding the distance to the object of interest is as simple as finding the pixels that corresponds to the lead vehicle and recording the distance from the model's depth prediction.

Location Estimating Demonstration: Our accident reconstruction procedure assumes access to GPS/IMU data that can be used to track the

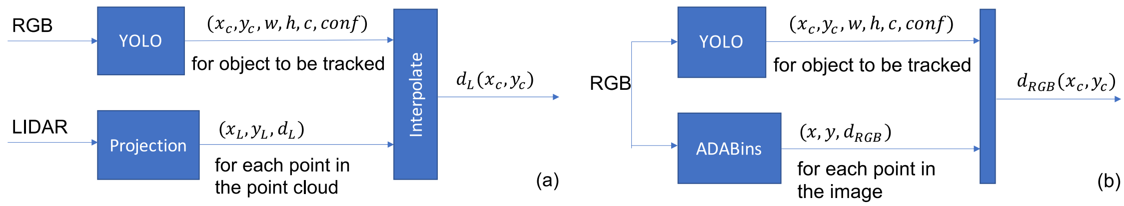


Fig. 5. (a) Data and processing pipeline using (a) both LiDAR and RGB images, and (b) only RGB images with AdaBins providing depth estimates.

location of the vehicle that contains the advanced sensors (LiDAR, radar, cameras). Given that this is a rather trivial procedure of reading the data from the GPS/IMU, here we focus on demonstrating the ability to track the position of an un-instrumented legacy vehicle with respect to the ego vehicle. For this purpose, two hundred consecutive data instances over 20 s were taken from the Kitti dataset, where a "lead" (legacy) vehicle is in front of the automated vehicle. The legacy vehicle is initially close to the automated vehicle, pulls away slightly, and then becomes close again by the 200th frame. Being able to track this behaviour is important for scene reconstruction as will be demonstrated in the next section.

First, the camera frame at each time instance is given to the 2D object detection model. Since the model will produce detections for every object class in the image, the user must specify which vehicle they are interested in. Because this scenario is a "vehicle following" scenario, we are interested in the movements of the vehicle closest to the centre of the image. Once the vehicle is identified, we can track, i.e., estimate the relative distance to that vehicle, either using both camera and LiDAR (Case 1) or with just camera data (Case 2).

The raw data, as well as the ability of our two image processing models, are summarized in Fig. 6. The output of our object detection model is shown in Fig. 6**a.** The LiDAR points in the dataset are projected over the image in Fig. 6**b**. The output of our camera-based depth estimation model is shown in Fig. 6**c**. The depths for both LiDAR and the estimation model are in the range of 0–80 m, as shown. Note that the distances for the depth model are only estimates based on the inner workings of the CNN behind the model, while the LiDAR values are direct measurements and thus can be assumed to be ground truth.

The results of tracking this vehicle are shown in Fig. 7. The 1st, 100th, and 200th frames are shown (at 0, 10, and 20 s respectively), and the distance calculations across time are plotted for both LiDAR (ground truth) and monocular depth estimation. Fig. 7 also provides a plot of the error between the ground truth LiDAR and the image-based depth estimation model. This demonstrates that even with the use of data from only a single monocular camera, a setup that is expected to be deployed on all automated vehicles, reliable estimates of relative distances and relative speeds can be obtained by training and using the correct deep neural nets. This also illustrates that all sensor modalities are not equally accurate, and the uncertainty incorporated by sensor and process (depth estimation model) noise may be relevant when trying to reconstruct the causes of an accident.

3.4. CARLA simulator

In the previous section, real world data was used to demonstrate the feasibility of our data pipeline toward effective visualizations. However, real-world data from accidents involving AVs are sparse, so in lieu of access to complete sensor data from actual AV involved crashes, simulation can be used to produce this data instead. To simulate AV-involved crashes, the CARLA simulation platform was chosen in this work (Dosovitskiy et al., 2017). CARLA is an open-source software enabling users to configure, simulate, and generate data from several AV sensors including LiDAR, cameras, radars, and GPS. CARLA is built on top of the Unreal Engine 4 graphical development kit that is specifically designed for AV simulation. Most features present in CARLA are intended for realistic and useful simulation and training of an autonomous vehicle's sensors and control algorithms. However, for the scope of this study, we present CARLA simply as a tool for collecting data in crashes involving a vehicle that is kitted with sensors such as lidar, radar, or cameras. In this

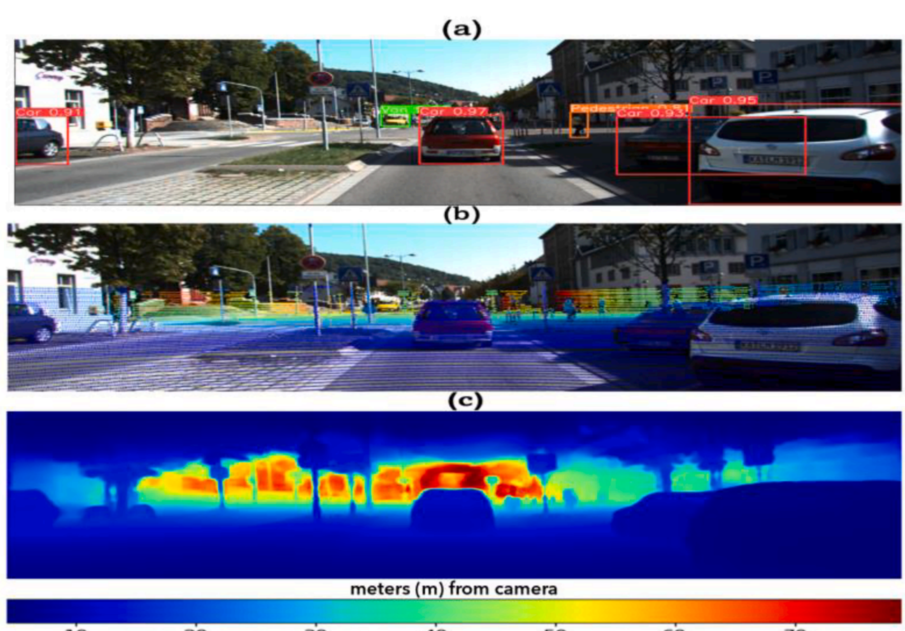


Fig. 6. A representative frame from the Kitti dataset and subsequent processing (a) Output of our YOLO object detector (b) The LiDAR points in the dataset projected over the image. (c) The output of our monocular camera-based depth estimation model (AdaBins).

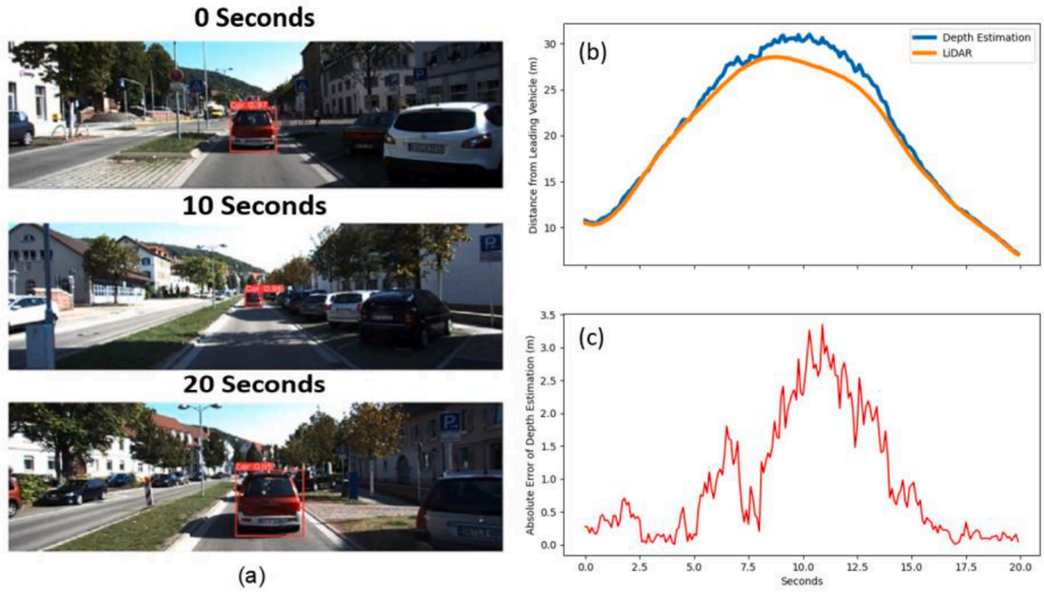


Fig. 7. To demonstrate the results of tracking a leading vehicle relative distance estimation on a driving sequence extracted from the Kitti dataset are shown (a) Sequence of frames – 1st, 100th and 200th frame, measured in seconds. (b) Distance to the leading car from the instrumented car across the tracking period measured from both the depth estimation network (blue) and LiDAR (orange). (c) Error estimate of visual depth estimator over time with LIDAR based depth as ground truth. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

scope, CARLA is used as a tool for crash recreation, data validation, or counterfactual scenarios quantification.

Regarding CARLA's dynamics, vehicles can be controlled by implementing custom vehicle software that controls the vehicle through data from simulated sensors and its measured dynamics. In lieu of implementing a complex control system that recognizes objects of interest such as vehicles, lane markings, etc. using computer vision algorithms, CARLA uses a robust lane keeping, car following and emergency stopping algorithm instead. In this scheme, waypoints are pre-programmed to indicate correct positioning for all driving lanes on the road. By supplying a destination waypoint, a simple proportional–integral–derivative (PID) controller was tuned that allows the CARLA vehicle to reach its destinations by controlling throttle, steering, and braking to minimize the error between its current position and the closet target waypoint on its set path. All vehicle dynamics in this study are controlled in this manner for the sake of simplicity, reliability, and repeatability.

3.5. Simulation scenarios

The CARLA simulations shown are simplified scenarios based on common elements found while analyzing the *California Tester Program* police reports.

CARLA Simulation #1: A cruise autonomous vehicle is driving on an urban street with a green jeep approximately 10 m behind it, with both vehicles accelerating to approximately 26 mph. A jaywalking pedestrian walks in front of the AV, triggering the AV to brake suddenly and avoid striking the pedestrian. The green jeep fails to stop, rear ending the AV. Both vehicles avoid contact with the pedestrian.

CARLA Simulation #2: A cruise autonomous vehicle is making a left turn with a green arrow in a four-way intersection. A conventional vehicle coming from the right with respect to the AV passes through the red light at approximately 45 mph. A mid-speed collision with the rear-right side of the AV is made in the middle of the intersection.

Data collected from these simulations are oriented to be precise, making simulation of real-world crashes such as this one a potential avenue for the public to obtain a clear picture of an event described by witnesses. In these scenarios, all vehicle and pedestrian positions are known with exact precision, all sensor data streams are synchronized perfectly, and the resulting simulation is perfectly repeatable. Table 3 illustrates that simple visualizations of the simulated sensor data or more complex object tracking outlined in the remainder of the paper can provide the information listed in the police report at a minimum.

3.6. Simulated sensor data

Our framework is intended to primarily accept camera, radar, and LiDAR data as input. These types of sensors are widely used in AV applications, and have varying benefits and weaknesses in different types of perception tasks (Boggs et al., 2019). All these sensors and their corresponding data types can be replicated inside CARLA with high level similarity with their real-world counterparts. For all data collection, our simulated AV was kitted with 4 sensors: 2 cameras, 1 LiDAR, and 1 rear facing radar, as well as conventional sensors that supply data regarding internal vehicle dynamics. Descriptions are provided below, with relevant parameters for each listed in Table 4.

LiDAR: Real world LiDAR data is generated by multiple lasers that rotate 360° around the sensor while calculating time of flight on the reflection of each laser. The result is a 3-D point cloud that can supplement other sensors such as cameras to provide the exact locations of objects in space. Of the sensors mentioned, LiDAR data is considered of the highest quality. The number of data points returned in a single scan

Table 3
CARLA Simulation Accident information.

Variable	CARLA Simulation #1	CARLA Simulation #2
Time	12:00 PM	7:00 PM
AV operation mode	Autonomous	Autonomous
AV Movement	Stopped	Turning Left
Legacy vehicle movement	Moving- Following- 0–27 mph	Moving- 40–45 mph
Collision type	Rear end	Rear-side
Weather condition	Clear	Cloudy
Lighting	Daylight	Low Light- Evening
Roadway condition	No unusual conditions	No unusual conditions

Table 4
Overview of the data being input to the pipeline. Parameters shown are for both *CARLA* Simulation #1 and *CARLA* Simulation #2.

Sensor	Data Type	Data size	Range	Update Rate
Camera	Image	480x720 pixels	≈ 10(detection)	60 Hz
Radar	3D point cloud (position + velocity)	≈ 300 oints	20 *m*	50 Hz
LiDAR	3D point cloud (position)	≈,000 points	50 *m*	50 Hz
GPS + IMU	Vehicle Position + Velocity	1 point	N/A	greater than60 Hz

of the sensor is often very rich, and the point cloud contains a relatively small amount of noise. In simulation, a laser can be represented by a 3D graphics tool called a "ray-trace", which can return the location of any object encountered along a straight line in the simulated world. Thus, simulated LiDAR is produced with essentially the same theory of operation as real LiDAR but without consideration of the physics of dispersion, diffraction, and reflection due to varying angles of incidence as well as material properties that affects the intensity of the reflected ray.

Radar: Radars are attached to many modern vehicles and allow for varying levels of automation. Radar also uses time of flight measurements of lower frequency waves to obtain the location of obstacles and are considered a cheaper solution than LiDAR but produce data that can be used for similar purposes. Simulated radar involves much of the same tools as simulated LiDAR. Ray tracing is used inside of CARLA to obtain object locations, and a series of functions are applied to the data to make it more realistic in comparison with physical radars, such as applying noise, transforming the data to a polar coordinate system, and inferring velocity data available on any radar sensors.

Front & Rear Facing Cameras: Just as in real cameras, these simulated cameras provide RGB (red, green, blue) images from inside the simulation. Cameras are relatively inexpensive to implement in AV applications but are computationally expensive to apply inside CARLA simulations. However, there are many tools to apply post-processing affects to the data that can allow us to achieve specific situational reconstructions in images.

Conventional Sensors (IMU, EDR, GPS): The conventional sensors provide data regarding the global position and vehicle dynamics of the vehicle. GPS will provide a known cartesian location for the vehicle in space. Vehicle speed and velocity can either be read directly from the IMU (Internal Measurement Unit) of the vehicle, or by differentiating the incoming data with respect to time.

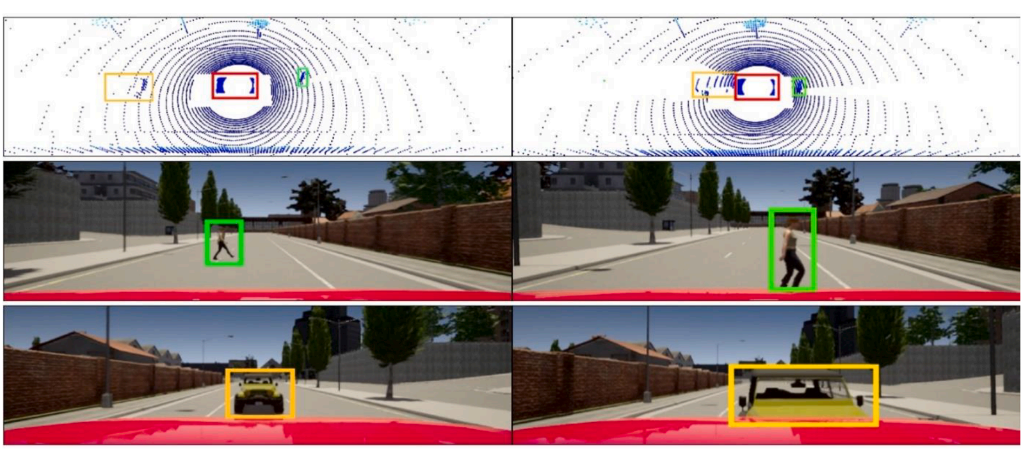
3.7. Data visualization

Many insights into crash behavior can be made by simply visualizing the output of this data pipeline with no further analysis. As shown in the data collected from *CARLA simulation #1*, we can see that multiple camera angles, as well as what amounts to a 360° representation from LiDAR and radar, are available for analysis with a minimal amount of technical post-processing. Fig. 8 shows a simple visualization of the data that can be obtained directly from an AV following a crash. This data is synchronized across all modalities, and in this case, shows all data obtained from the vehicle in the moments prior to rapid deceleration of the AV, as well as the moment after collision. Visualization such as what is shown in Fig. 8 can be done easily and rapidly. Making this data available to investigators following an accident could allow a rapid and accurate understanding of what took place, verifying or alleviating the need for witness testimony.

In crash analysis, it is important to understand the totality of events that culminated with the crash. Vehicles with autonomous capabilities do not typically have cameras with full 360-degree vision around the vehicle. However, the multiple sensor modalities on board the vehicle can be visually combined to show the complete picture. Fig. 9 shows a complete visualization of *CARLA Scenario #2*. By combining multiple sensor modalities, we can reach a larger number of conclusions about the crash. For instance, we can see that the AV had the right of way with the green arrow when turning left. We also conclude that the lidar was able to locate the incoming vehicle almost a second before the rear camera saw the vehicle. All of this data can be displayed side-by-side with the trajectories of the vehicles for a complete picture of the crash, while any one sensor would be insufficient.

3.8. Data analysis for detailed crash reports

As shown in the previous section, a simple visualization of the data that is available following an accident involving an AV can provide valuable information that may or may not be available directly from investigation or witness testimony. However, in the case of AVs, it is extremely likely that the investigation may need to understand how the AV and humans in an accident responded before, during, and after an accident at a deeper level. When did the vehicles react? Did the AV brake too suddenly? Did the human drivers have enough time to react to the AV? Such questions can be answered by applying simple data analysis and readily available tools to the collected data. Fig. 10 shows positional



(a) (b)

Fig. 8. Visualization of CARLA sensors in *CARLA Simulation #1*. LiDAR and Radar (Top), front-facing camera (middle), rear-facing camera (bottom) are shown. Frames are displayed a) 1.14 s before collision and b) at vehicle impact. Pedestrian (green), following vehicle (orange), and AV (red) are color coded for all sensor modalities. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

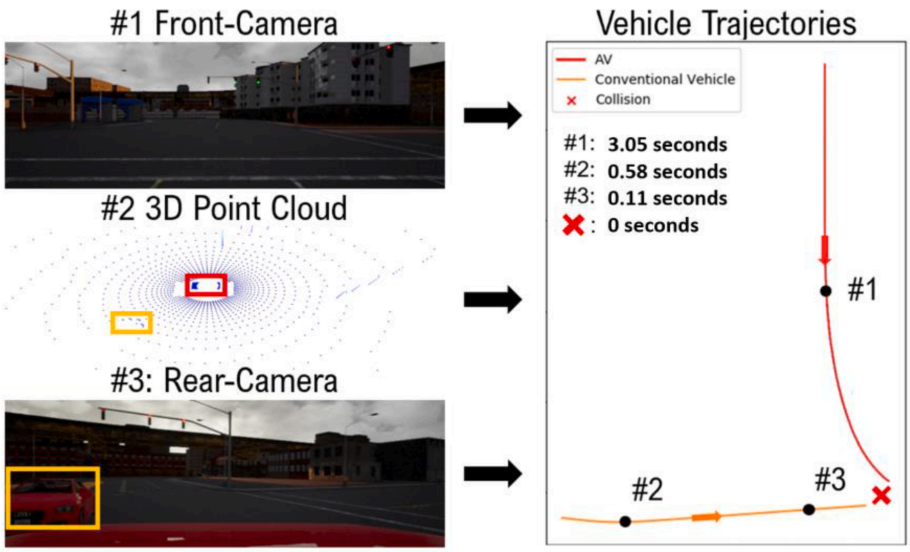


Fig. 9. Visualization of *CARLA Simulation #2.* Times shown are in seconds before collision. Following vehicle (orange), and AV (red) are color coded for all sensor modalities. Visual data collected (left) can be used to supplement scene dynamics data (right) for a clear understanding of the crash, even when any one sensor is not sufficient. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

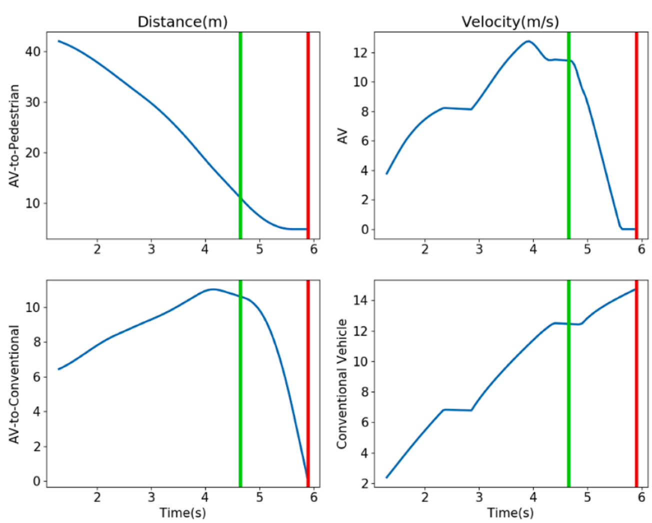


Fig. 10. Positional and velocity information of vehicles prior to collision. The green and red vertical lines indicate the time instants at which the frames displayed in Fig. 7a and 7b were collected respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

and velocity information that would typically not be available in EDR data, which only consists of vehicle kinematics pertaining to the vehicle kitted with sensors and does not contain any trajectories of surrounding vehicles, pedestrians, or bicyclists, and environmental conditions such as rain or snow.

In Fig. 10, the six seconds prior to collision are plotted. distance from AV to pedestrian (top left), AV velocity (top right), distance from AV to colliding conventional vehicle (bottom left), and velocity of the conventional vehicle (bottom right). The green and red vertical lines indicate the time instants at which the frames displayed in Fig. 7a and 7b were collected respectively. It is obvious in Fig. 10 that the conventional vehicle following from behind never applied the brakes, as its velocity never decreased. Simple numerical analysis can be valuable as well, such as observing that the AV slowed from approximately 12 m/s to a complete stop in just over a second. More complex analysis on AV sensor data can certainly be done, but this illustrates the value in applying simple techniques to AV sensor data analysis. For crash investigators, we will need to develop procedures and protocols that will facilitate obtaining and analyzing such data. The results clearly show a more complete picture of pre-crash scene and factors contributing to the crash.

4. Limitations

As mentioned previously, simulations and synthetic data are typically considered simplified or idealized versions of their real-life counterparts. In the construction of this simulation, there are no doubt many relevant details present in the actual crash that are both present and not present in the police report. While there are tools and techniques for accounting for an increasing number of variables as well as making sensor data more realistic, it is important to note that simulation tools such as CARLA used in this research as a supplement to real data collected on AVs and not as a replacement. Specifically, if any conclusions are to be drawn about the performance of object recognition algorithms or vehicle dynamics using simulation, careful consideration needs to be given to proper domain transfer of the synthetic data to faithfully resemble real data, as well as a complete understanding of the vehicle kinematics and the dynamics model deployed in the simulation. Also, for the demonstration purposes of our simulations, object recognition was done using tools built-in with CARLA as well as manual annotation. As such, error associated with any of the object detection algorithms implemented within this framework will be found within the visualizations that are not demonstrated here.

5. Conclusions

This study applies the safe systems approach for understanding automated vehicle safety by showing how different AV databases can be used in crash investigations. Specifically, the study contributes by demonstrating how new automation technologies, especially sensors on AVs that include cameras, LIDAR, and Radar can provide valuable data to help in the identification of contributing factors, such as driver, vehicle, and roadway/environment factors. The feasibility of combining modalities in our data pipeline was demonstrated on the Kitti dataset.

By using AV-involved crashes in California and simulating them in CARLA, the study demonstrates the value added by the AV sensors for crash investigations. Next, we show how the raw data from the sensors described can be visualized, and how these visualizations can impact the study of AV involved accidents. The study demonstrates how LiDAR, cameras, and Radar sensors can provide crash investigators with new information about the state of the driver, the movement of vehicles, trajectories of other moving objects or people and the surrounding objects. Using the real-life crash, the study further develops counterfactuals, e.g., if a pedestrian was crossing in front of the AV and how this situation can change the dynamics and outcomes of crashes.

The conclusions in this study are based on new and emerging data which can transform crash investigations. The simulation and data analysis provides rich insights. The study showcases and points to developing protocols about the analysis of sensor data from AVs. This can impact future crash investigations, which are carried out by various stakeholders that include private companies, police investigators, and the legal system that deals with vehicle crash liability issues.

This study does not use data from Basic Safety Messages or any V2V or V2X type communications data used for coordination between CAVs and/or smart infrastructures. Specific crashes involving multiple AVs might benefit from tapping into BSMs to study the pre-crash information exchanges and the corresponding responses from the two AVs. This study did not include this communication modality but was strictly restricted to data from AV sensor suites only. Future research can harness BSM data on vehicle kinematics. The study did analyze the latest information on AV crashes that have occurred in California.

CRediT authorship contribution statement

Joe Beck: Methodology, Software, Validation, Formal analysis, Writing – original draft, Visualization. **Ramin Arvin:** Methodology, Data curation, Writing – original draft. **Steve Lee:** Methodology, Formal analysis, Data curation, Writing – original draft, Visualization. **Asad Khattak:** Conceptualization, Writing – review & editing, Project administration, Funding acquisition. **Subhadeep Chakraborty:** Conceptualization, Writing – review & editing, Project administration, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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