

ADAS TESTING IN CANADA: COULD PARTIAL AUTOMATION MAKE OUR ROADS SAFER?

Eric Meloche
Dominique Charlebois
Benoit Ancil
Transport Canada
Canada

Guillaume Pierre
Annie Saleh
PMG Technologies
Canada

Paper Number 19-0339

ABSTRACT

As part of an ongoing effort to further improve the safety of its road transportation system, Transport Canada (TC) has been evaluating Advanced Driver Assistance Systems (ADAS) for a number of years now. The main objective of this paper is to determine the potential of ADAS technology in reducing fatalities and injuries on Canadian roadways while using proven international test protocols and certified test equipment. The findings will be used to provide science-based evidence in support of future regulatory, research and policy development.

Results from this study clearly demonstrated that Automatic Emergency Braking (AEB) and Pedestrian AEB (P-AEB) technologies can provide significant improvements in terms of collision mitigation which can directly result in reduced road fatalities and injuries. These findings are also in line with those of studies based on real-World data predicting significant reductions in rear-end collisions due to AEB deployment.

Nonetheless, this ADAS program also exposed an important number of flaws and performance variability. While the best AEB and P-AEB systems were able to fully avoid collisions with vehicles and pedestrians at speeds up to 60 kilometers per hour (km/h), others were challenged at speeds below 10 km/h. Also, a few P-AEB systems were never able to avoid a collision with a pedestrian despite manufacturers' claims of pedestrian avoidance capabilities. Scenarios replicating AEB activation in moving traffic showed that most systems unnecessarily came to a full stop rather than match the speed of vehicles they detected on their path, potentially generating higher safety concerns than those they were designed to prevent in high density traffic. Finally, due to variability in test results and overall unpredictable system behaviour, it was not possible to gather enough data to confidently assess the potential safety benefits associated with Lane Support Systems (LSS).

AEB, P-AEB and LSS are essential components of automated driving systems which will need to reliably brake and steer at all time to safely avoid other road users. That level of performance is not yet evident from the extensive testing carried out within this project. Substantial progress is therefore needed to reach the level of detection, braking and steering performance that will be required to make commercial automated driving systems a reality.

INTRODUCTION

At the time of writing, Transport Canada (TC) had just released its latest motor vehicle collision statistics report which is generated every year from the National Collision Database (NCDB). The NCDB contains detailed information from all police-reported motor vehicle collisions that occur on Canadian roads. According to this report, fatalities, severe injuries and total injuries were at an all-time low in 2017. TC started collecting these data in the early 70's when fatalities were almost 4 times greater than what they are today despite a much lower count in licensed drivers and registered vehicles. Thankfully, with the advent of effective safety policies and technological advancement, amongst things, Canadian motorists have been witnessing a continued improvement in road safety for nearly five consecutive decades. However, even if statistics showed a downward trend in casualties for 2017, 1,841 people still lost their lives due to traffic-related collisions across the nation while 154,866 suffered injuries [1].

As part of a constant effort to further improve the safety of its road transportation system, TC has been evaluating crash avoidance technologies and Advanced Driver Assistance Systems (ADAS) for several years now. In short, ADAS technologies are the building blocks of full automation and include a wide variety of active safety features that can assist drivers in: applying the brakes automatically if an imminent crash is detected; keeping a vehicle on its traveling lane; detecting vehicles in a blind spot; or keeping a safe distance from vehicles ahead. Some of the World-leading safety experts believe that the greatest gains in highway safety in the coming years will result from a widespread application of crash avoidance technologies [2] [3].

An in-depth analysis of the latest statistics extracted from the NCDB revealed that the most frequent occurrences in which current driver assistance technologies could offer either full or partial mitigation measures was rear-end collisions (25% of collisions with casualties) while those offering the best potential for saving lives correspond to road departures (17% of fatalities) and collisions involving vulnerable road users (17% of fatalities). The latter being composed of pedestrian (15% of fatalities) and cyclists (2% of fatalities). 746 of the collisions involving fatalities (44%) and 85,993 of those involving personal injuries (74%) took place in urban settings while the remainder occurred in rural areas.

While several ADAS technologies are currently being evaluated by TC, this study will specifically focus on the assessment of Automatic Emergency Braking (AEB), Pedestrian AEB (P-AEB) and Lane Support Systems (LSS). These particular technologies were intensively investigated as they were deemed able to offer substantial safety benefits in the high risk areas previously identified. The findings of this study will be used to provide science-based evidence in support of future research, regulatory and policy development.

METHODS

The crash avoidance technologies investigated in this study use sensors such as radars, lidars, ultrasonic or cameras to scan the road ahead or surrounding a vehicle and detect potential conflicting situations. In order to properly evaluate each system, these conflicts need to be reproduced with high repeatability in controlled environments. The following sections will describe the protocols, equipment and methodology used to perform these evaluations.

Systems Tested

AEB and P-AEB systems are designed to prevent crashes or reduce their severity by braking automatically when an imminent collision is detected and the driver fails to react on time, or at all. They are characterized by 3 different functionalities: Forward Collision Warning (FCW) which warns a driver when a conflicting situation is detected; Crash Imminent Braking (CIB) which applies the brakes automatically if a driver fails to respond to the warning on time; and Dynamic Brake Support (DBS) which provides supplemental braking power if a driver does respond to the warning on time but does not brake hard enough.

LSS incorporates a group of technologies designed to assist drivers in keeping their vehicles on their traveling lane. They include Lane Departure Warning (LDW), Lane Keeping Assist (LKA), Lane Centering Systems (LCS), Emergency Lane Keeping (ELK), and others. The current evaluation will focus on LDW and LKA.

Test Vehicles

During the course of this program, approximately 100,000 km of combined on-road and track testing were conducted by TC and its contracting partner PMG Technologies on 36 different ADAS-equipped vehicles. Caution was taken to assemble a test fleet that was as diverse as representative of the real-world Canadian fleet. The vehicles selected ranged from model year (MY) 2012 to 2018 and were sourced from every manufacturers selling light passenger vehicles in Canada under 24 different brands. With the exception of a 2017 Volvo XC90 and a 2016 Tesla Model S, which were graciously lent by Volvo Canada and Environment and Climate Change Canada (ECCC), the test vehicles were acquired by TC. No details about the programs were communicated throughout the procurement process to ensure that the vehicles remained comparable to those available commercially. Table 1 provides the detailed list of vehicles used in this study.

Table 1.
Transport Canada ADAS Test Vehicle Fleet

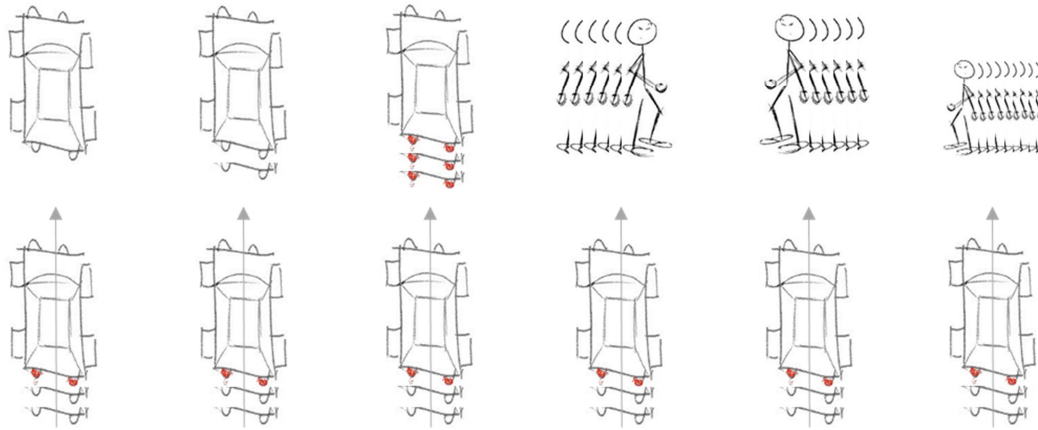
Manufacturer	Test Vehicles
Ford Motor Company	Ford Focus, Lincoln MKX, Ford Fusion
General Motors	Chevrolet Impala, GMC Acadia
Toyota Motor Corporation	Toyota Prius PHEV (2), Toyota Corolla and Toyota Highlander
FCA	Jeep Grand Cherokee, Chrysler 200, Fiat 500X, Chrysler Pacifica
Honda Motor Company	Honda CRV, Honda Civic
Hyundai Kia Auto Group	Hyundai Genesis, Hyundai Elantra and Kia Sportage
Nissan Motor Co	Infiniti Q50 and Mitsubishi Outlander, Nissan Rogue
Volkswagen Group	Audi A3, Volkswagen Golf
Mazda	Mazda 6
Subaru Corporation	Subaru Legacy, Subaru Outback, Subaru Impreza, Subaru Crosstrek
Daimler	Mercedes-Benz C400, Mercedes-Benz E300
BMW Group	BMW i3
Tesla	Tesla Model S
Jaguar Land Rover	Land Rover Discovery Sport
Volvo	Volvo S60, Volvo XC90, Volvo XC60

Test Procedures and Protocols

For comparison and validation purposes, the work carried out in this study was based primarily on test procedures developed by the National Highway Traffic Safety Administration (NHTSA) [4] [5], the International Organization for Standardization (ISO) [6] [7], the European New Car Assessment Program (Euro NCAP) [8] [9] [10], as well as the Insurance Institute for Highway Safety (IIHS) [11] [12].

Table 2 shows the test scenarios used for both the AEB and P-AEB evaluations. A total of 4 scenarios were used to evaluate the CIB and DBS variants of AEB in static and dynamic modes: a moving car approaching a stopped car (A1) representing a car stopped at a red light, at a stop sign or in traffic; a fast car approaching a slow car (B1 / B2); and an emergency stop where two cars are traveling at the same speed in close proximity and the lead car brakes suddenly (C1). 4 scenarios were also used for P-AEB testing: a running adult crossing the path of a car far-side (CPFA-50) with a theoretical impact point located at 50% of the width of the car (median); a walking adult crossing the path of a car near-side (CPNA-25 / CPNA-75) with a theoretical impact point located at 25% / 75% of the width of the car (passenger side / driver side); and a child running from behind two near-side road-side obstructing vehicles (CPNC-50) with a theoretical impact point on the median. The target and vehicle speeds required for each scenario are provided in Table 2 while more details can be found in the above-mentioned test procedures.

Table 2.
AEB and P-AEB Test Scenarios

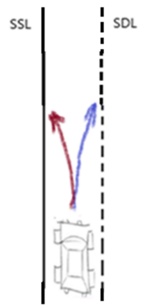
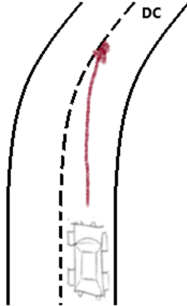
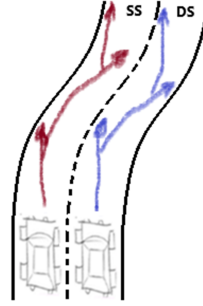


Test Scenario	STATIC A1	DYNAMIC B1 / B2	DYNAMIC C1	PED CPFA-50	PED CPNA-25/75	PED CPNC-50
Target Speed (km/h)	0	16 / 32	56	8	5	5
Vehicle Speed (km/h)	0-50	40 / 72	56	0-50	0-50	0-50

There are over 1 million kilometers (km) of roads in Canada with varied state of maintenance and quality [13]. These include 17,000 km of expressway and a total of 415,600 km of paved roads. A mixture of road segments from TC's Motor Vehicle Test Center (MVTC) which were judged representative of this vast road network were selected for the LSS evaluation. 3 different scenarios were used to evaluate the 10 different systems included in this study. The first was a drifting scenario in a straight line where a vehicle would drift towards a shoulder lane (SSL) or towards a dotted center lane (SDL) [10]. The second scenario was a vehicle entering a 493 meters (m) radius curve towards a dotted center lane (DC) [7]. The third scenario was an S-Curve course that forced the vehicle to react to a left and right lane marking consecutively (based on Scenario #1 and #2). In the Doted S-Curve scenario, the vehicle encounters the dotted line first (DS) while in the Solid S-Curve scenario, it encounters the solid line first (SS). All 3 scenarios are illustrated in Table 3.

The surface type for both Straight Line and the S-Curve scenarios was asphalt with white dotted center lines and solid yellow shoulder lanes. The Curve scenario was performed on a concrete section of a high-speed track with the same paint configuration. The road markings were mapped using an Oxford Technical Solutions (OxTS) RT 4002 system and imported into an RT-Range system to have a 2D representation of the test bed. The outer edges of the vehicles' tires were also measured and digitalized into the system to increase precision. This method allowed testing under various weather condition while always providing vehicle's position with respect to the lane markings.

Table 3.
LSS Scenarios

Scenario #1	Scenario #2	Scenario #3
		
Straight Solid Line (SSL) and Straight Dotted Line (SDL)	Dotted Curve (DC), 493 m radius	Dotted S-Curve (DS) and Solid S-Curve (SS), 1,219 m radius
Entering Gate at 72 km/h		

Test Equipment

The targets used for the AEB evaluation included the Euro NCAP Vehicle Target (EVT), the NHTSA Strikeable Surrogate Vehicle (SSV) and the Euro NCAP Global Vehicle Target (GVT) coupled to the Guided Soft Target (GST) system from Anthony Best Dynamics (ABD). The P-AEB evaluation used the Euro NCAP pedestrian targets (50th percentile adult male (EPTa) and 7-year-old child (EPTc)) paired with the Soft Pedestrian Target (SPT-20) system from ABD. All of these systems were used in accordance with the test protocols previously described. Figure 1 shows the evolution of the test targets used in the Crash Avoidance program. From left to right: TC/PMG's inaugural "pendulum" vehicle surrogate target (not included in analysis), the EVT, the SSV, the EVT in winter testing condition, the GVT and to complete, the full family of pedestrian dummies.



Figure 1: Surrogate Targets used in AEB and P-AEB Evaluation Programs

The test vehicles were instrumented with RT4002 Inertial GPS Navigation Systems and RT-Range from OxTS to measure vehicle position and heading, vehicle speed and angular velocities (yaw, roll, and pitch rate), linear acceleration (longitudinal, lateral and vertical), distance to target and relative velocity. The accuracy of the GPS was augmented through the use of a portable GPS Base Station. To increase accuracy and repeatability of crucial longitudinal test parameters (i.e.: throttle input, braking input, velocity, headway), test and target tow vehicles were fitted with Combined Brake and Accelerator Robots (CBAR) from ABD. All lateral test parameters were controlled by the test drivers.

Test Methodology

The methodology used for the AEB evaluation was based on both the CIB and DBS procedures designed by NHTSA [4] [5] with the only exception that static tests (A1) were performed at speeds within the range of 10 km per hour (km/h) to 50 km/h (to allow comparison with Euro NCAP) rather than only at 40 km/h. In order to reduce the number of tests required to complete each vehicle's assessment and preserve the test equipment's integrity the following strategy was followed: the vehicle was driven at an initial speed of 20 km/h; if there was no impact, the

speed was then increased in increments of 10 km/h up to the maximum speed of 50 km/h; if an impact occurred, the speed was reduced by 5 km/h. A series of tests was considered valid if no impacts were observed in at least 5 out of 7 tests. If 3 impacts occurred before reaching 5 out of 7 tests without impact, the vehicle speed was reduced by 5 km/h. The goal was to determine the maximum avoidance speed of the systems. The test speed chart used for the static AEB scenario and all 4 P-AEB scenarios is shown in Figure 2.

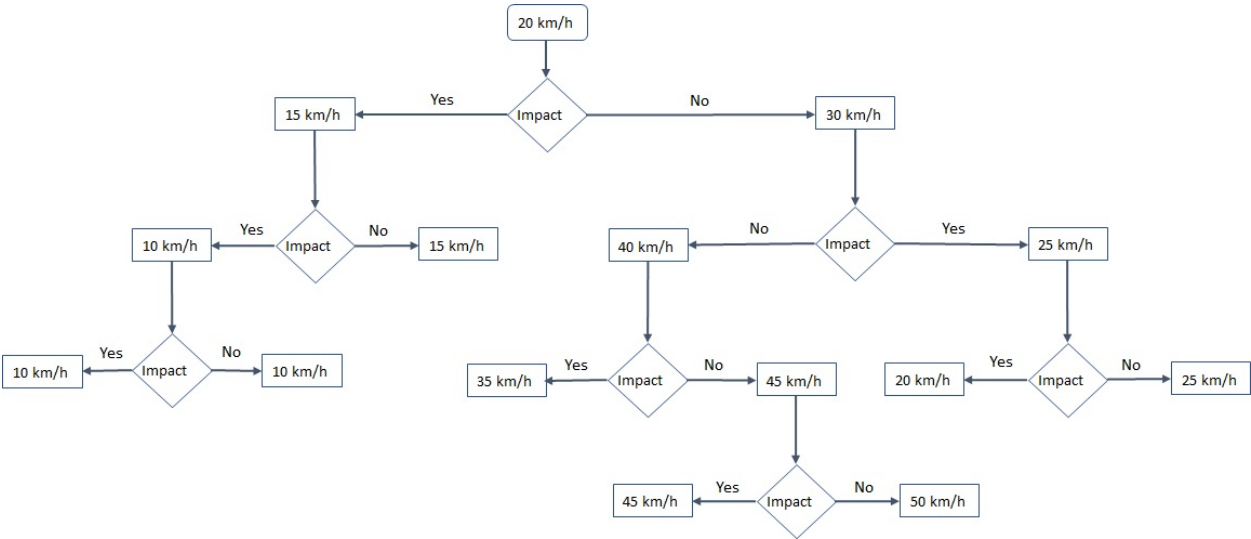


Figure 2: Test Speed Chart for Static AEB and P-AEB Evaluation Programs

The procedure used for the LSS evaluation was based on existing American and European test protocols and was designed to capture the LSS behaviours of 10 vehicles from TC’s test fleet. It consisted of 5 repetitions of each test scenario (Table 3) with cruise control “on” and with cruise control “off”. If the results with and without cruise control were similar, the tests were only performed 3 times in the “off” configuration. Vehicles were tested with LKA system active and inactive. Haptic signals were collected via an accelerometer on the steering wheel and audio signals via a sound probe.

The data collected during the LSS testing included: environmental conditions; offset from lane marking at warning; distance travelled from the entrance gate at warning; ambient temperature; wind speed; wind direction; the type of warning (visual, audio, haptic); test speed; and state of cruise control (on/off). The warnings were produced visually for most of the vehicles tested.

In the winter of 2019, TC started assessing the performance of LSS on snow covered roads (Figure 3). The method consisted of: creating tire tracks to produce a contrast with the surrounding environment after a snow fall; and try to engage the LSS while driving on this portion of road. 4 vehicles were tested and none of them were able to fully engage and recognize the road path. This type of condition is typical of Canadian roads in winter.



Figure 3: Road Surfaces for LSS Testing

RESULTS

This study includes the comparative analysis of 7,710 individual crash avoidance tests obtained from 36 specimen vehicles equipped with automatic emergency braking, pedestrian automatic emergency braking and lane support systems. Over 100,000 km of combined on-road and track testing were conducted with these vehicles in a wide range of climate conditions replicating the Canadian landscape in the best possible way (standard conditions, direct sun, darkness, rain, fog, ice, and snow).

Automatic Emergency Braking (AEB) Test Results

All AEB systems tested during this evaluation were evaluated for both their CIB and DBS variants. The complete test matrix included 4 test scenarios (A1, B1, B2, C1) to be tested at a potential of up to 5 different speeds in static configuration and at one single speed in each of the dynamic scenarios. All 3 targets (EVT, SSV, GVT) were typically used for standard or rainy conditions when possible. The EVT was the only target used during the winter testing portion of the program and only the static test scenario (A1) was conducted on dry, ice and snow surfaces. The speed reductions and maximum avoidance speed presented in the Tables and Figures below consist of an average of 5 out of 7 tests as previously described.

AEB Maximum Avoidance Speed. Figure 4 shows the maximum avoidance speed achieved by each of the test vehicles in this evaluation. Some of the best systems were able to fully avoid a rear-end collision at speeds in excess of 60 km/h while others were challenged by speeds below 10 km/h. This exercise demonstrated that all systems were not designed equally and that some were not even capable of avoiding a collision at all in static scenarios. 2 of the test vehicles could not avoid a collision at any speed while 6 of them were able to avoid a collision at 50 km/h. In general, the evaluation of the CIB and DBS variant of the systems would produce similar results but for a few specimens, the level of performance measured in the DBS configuration far exceeded the level of performance measured in the CIB configuration (Table 4). For instance, one of the 2 vehicles that could not avoid a rear-end collision at any speed in the CIB configuration was able to avoid a collision at 50 km/h in the DBS configuration.

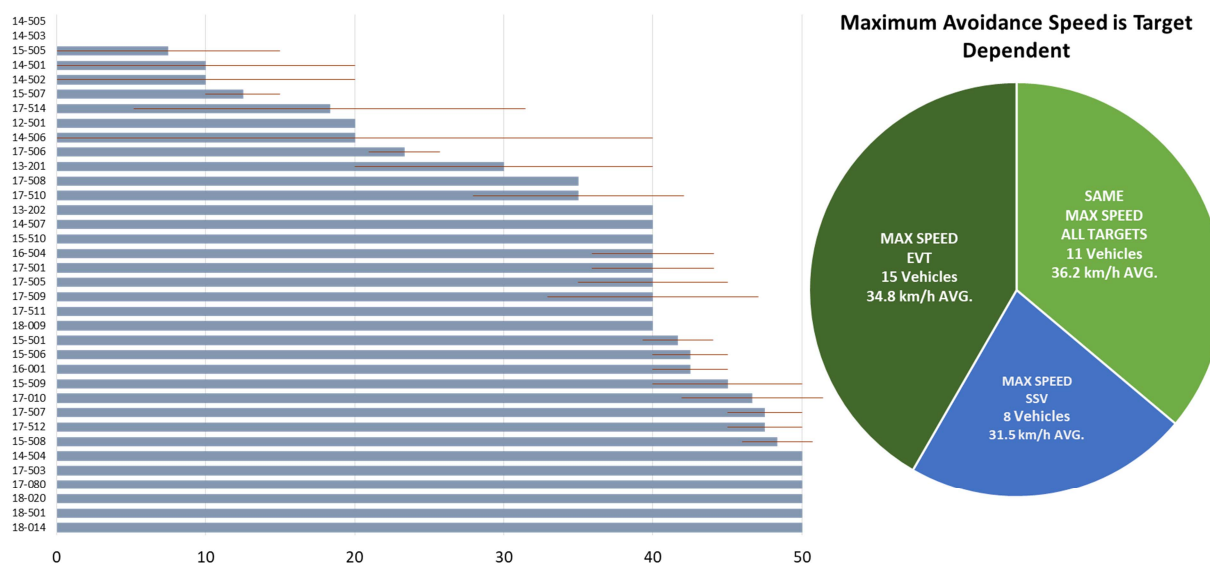


Figure 4: Maximum Avoidance Speed of 36 AEB Systems, CIB Configuration (km/h)

The maximum avoidance speed measured for each of the test vehicles as proven to be target dependent. The maximum avoidance speed was highest when tested with the EVT for 15 vehicles while 8 vehicles reached higher avoidance speeds when tested with the SSV. This could potentially be explained by the fact that a large amount of

manufacturers had indicated that their systems were developed using the EVT. For 11 of the systems tested, the test target had no influence on the maximum avoidance speed and 2 vehicles had similar results with at least 2 out of the 3 targets. The test to test variation is also illustrated by the error bars on the chart of Figure 4.

AEB Maximum Speed Reduction. Table 5 lists the speed reductions achieved by each of the AEB systems in their CIB configuration. The results were organized in a way to provide a good visual representation of the overall test fleet performance. Results are presented in increments of 5 km/h for each target and a scale of green tones was created to rank the level of speed reduction achieved for every target speed. This scale would attribute the color light grey for a speed reduction of 0 km/h (severe impact) or test speeds that were not conducted due to repeated impacts at lower speeds, the color light green for a low speed impact and the color dark green for a full avoidance or 100% of the expected speed reduction. The dark grey zones indicate scenarios that were not conducted. The results were then organized in chromatic order with the darker shades from top to bottom. A simple look at this table provides a good overview of what can generally be expected from AEB technology in terms of speed reduction and associated safety benefits as its deployment in the field is in constant progression. To sum up, the greener, the better.

The overall results suggest that 7 or 8 test samples that found themselves at the bottom of the chart did not seem to perform as well as the average of the rest of the fleet. However, when comparing these results against established performance criteria, 24 out of the 36 AEB systems evaluated achieved a level of performance sufficient to meet all the requirements set forth in NHTSA's CIB test procedure, as shown in Table 6. Concurrently, only 2 of the systems did not meet the minimum performance requirement used for the voluntary memorandum of understanding (MOU) signed between IIHS, NHTSA and the car industry for a commitment to make AEB a standard feature by 2022 in the United States (U.S.). This minimum requirement consists of a subset of NHTSA's requirement for the static test with the option of achieving a speed reduction of 15.8 km/h in either a 20 km/h or 40 km/h test or achieving a speed reduction of 7.9 km/h in both tests. Again, one of these two specimens was found to meet NHTSA's minimal performance requirements when evaluated in the DBS configuration.

As many manufacturers indicated that their system would perform better in scenarios where a target is in motion, it was expected that the level of performance would be greater for the dynamic scenarios. The chromatic scale used in Table 5 demonstrates this quite eloquently as very few areas of the 16-40 (B1), 32-72 (B2) and 56-56 (C1) columns are labelled in light grey. However, amber and red shaded cells do appear in the B1 and B2 columns. As many of the systems did bring the vehicles to a full stop instead of modulating their speed to that of the target they detected on their path, these amber and red shaded areas represent excessive speed reductions or over-braking. For every speed reduction that exceeded 24 km/h in the B1 scenarios or 40 km/h in the B2 scenarios (with a slight tolerance for both cases) a scale of amber to red tones was created. The color amber is associated with mild excessive deceleration and the color red is associated with severe excessive deceleration or a full stop. This representation is not absolutely perfect as it includes cases where vehicles did not produce excessive braking because of their system design but simply because they crashed with a target, or a vehicle if this was to be transposed in the real world. Nevertheless, this demonstrates a scenario where, if in high density traffic, AEB systems could potentially generate safety concerns which are greater than those they can prevent.

Table 4.
Vehicles with better Maximum Avoidance Speed in DBS than CIB (km/h)

Vehicle	EVT (A1)		SSV (A1)	
	CIB	DBS	CIB	DBS
14-505	0	50	0	50
16-504	40	50	30	50
17-506	25	50	20	50

AEB Performance Criteria. Table 6 provides a list of performance requirements used for the assessment of AEB systems. All requirements presented in this table are in accordance with those of NHTSA's CIB test procedure. One additional requirement for the static test scenario (A1) was also included to allow for direct results comparison with the Euro NCAP test protocol [8].

Table 5.
Speed Reductions Provided by 36 AEB Systems, CIB Configuration (km/h)

Test Vehicle	EVT A1								B1	B2	C1	SSV A1								B1	B2	C1	GVT A1								B1	B2	C1				
	20	25	30	35	40	45	50	40	72	56	20	25	30	35	40	45	50	40	72	56	20	25	30	35	40	45	50	40	72	56							
18-020	19	-	29	-	39	44	48	28	45	55	19	-	29	-	39	-	49	29	47	56	21	-	30	-	39	44	50	34	44	56							
17-503	19	-	30	-	40	-	49	36	58	56	20	-	30	-	39	-	49	38	64	55	20	-	30	-	40	-	50	35	55	56							
17-504	-	-	29	-	38	-	48	37	48	55	18	-	29	-	38	-	48	37	51	55																	
17-507	19	-	29	-	39	-	49	40	48	50	20	-	29	-	39	41	33	34	57	47					-	-	-	-	-	41		-	-				
18-501	-	-	-	-	39	-	49	37	65	46	-	-	-	-	39	-	49	37	48	48									-	-	-	-	-	-	37	48	51
18-014	19	-	29	-	39	44	48	39	51	55	19	-	29	-	39	-	49	-	-	-					20	-	30	-	39	-	50	-	-	-			
17-010	20	-	30	-	39	44	47	35	48	52	20	-	30	-	40	-	43	39	55	54					20	-	30	-	40	-	-	37	48	53			
13-201	20	-	30	-	40	-	50	40	71	48	20	-	30	-	40	-	50	40	72	45																	
15-509	-	-	-	-	39	-	49	39	56	55	19	-	29	-	39	45	49	39	63	56					-	-	-	-	-	45	-	-	-	-			
15-501	-	-	-	35	34	44	46	20	67	46	-	-	-	-	37	40	38	23	57	46					19	-	-	-	-	40	40	41	30	49	38		
14-504	20	23	27	-	40	-	50	37	64	42	-	-	-	35	40	-	49	35	61	35																	
16-504	20	-	30	-	40	44	34	29	41	53	-	-	30	34	34	-	-	30	29	38					19	-	30	35	36	-	-	37	26	33			
17-501	-	-	-	-	39	33	41	40	66	56	15	-	30	-	39	43	41	29	40	52					19	-	30	35	38	43	-	30	45	47			
17-505	20	-	29	-	40	45	45	38	48	49	13	-	30	33	33	-	-	34	25	40																	
15-508	10	-	30	-	40	45	48	40	70	48	19	22	25	33	33	-	48	37	65	48					-	-	30	-	38	-	42	37	45	50			
17-512	13	-	30	-	40	45	44	36	61	24	-	25	30	-	40	32	31	36	60	17					-	-	-	-	-	32	-	-	-	-			
15-506	-	-	-	-	38	45	43	40	67	33	-	-	28	25	26	16	-	40	72	33																	
17-511	20	-	30	-	39	39	30	40	65	29	-	-	30	-	40	39	32	32	45	21					20	-	27	27	39	39	-	40	36	23			
14-507	16	17	14	-	32	-	23	25	43	22	14	20	27	35	40	45	24	27	32	27					-	-	-	-	-	45	-	-	-	-			
18-009	20	-	30	-	40	18	19	36	32	48	16	-	30	-	40	18	-	39	42	45					10	-	30	-	40	18	17	38	37	48			
16-001	19	25	28	35	40	38	-	37	45	53	19	25	-	35	-	44	38	23	37	40					-	-	-	-	-	44	-	-	-	-			
17-510	20	25	30	-	36	34	-	19	49	56	-	25	30	32	33	-	-	32	48	49					-	25	19	-	31	-	9	28	37	56			
17-509	20	-	30	35	32	-	-	40	70	56	20	-	30	-	40	-	50	39	67	56					-	-	29	33	29	-	-	40	49	46			
13-202	20	-	30	35	30	-	-	36	44	35	20	-	30	29	27	-	-	40	40	40																	
17-514	20	-	30	17	11	-	-	36	42	51	20	24	21	-	-	-	-	39	67	42					-	-	-	-	-	-	-	40	53	41			
15-510	-	-	30	22	21	-	-	40	28	29	-	23	26	20	21	-	-	-	-	-																	
14-506	19	25	19	-	16	-	-	32	27	17	-	24	19	-	16	-	-	40	20	18																	
17-506	20	23	15	-	-	-	-	22	14	13	20	17	13	-	-	-	-	10	11	13					-	25	17	-	-	-	-	-	-	-			
17-508	-	-	-	-	-	-	-	33	17	-	-	-	29	33	26	-	-	18	13	6																	
14-501	-	18	-	-	-	-	-	-	-	-	20	-	-	-	-	-	-	-	-	-																	
14-502	17	12	11	3	4	-	-	18	31	-	-	-	-	-	-	-	-	31	33	-																	
14-503	10	4	9	9	7	-	5	13	8	12	-	-	-	-	-	-	-	30	63	11																	
14-505	5	-	-	-	6	-	-	14	16	17	2	-	-	-	-	-	-	11	11	19																	
15-505	14	11	11	-	11	-	-	11	6	14	11	-	-	12	12	-	-	10	8	-																	
15-507	6	7	17	-	-	-	-	36	26	24	16	24	17	-	-	-	-	24	24	21																	
12-501	17	11	-	-	-	-	-	-	-	14	12	8	4	-	-	-	-	40	-	-																	

Table 6.
Crash Imminent Braking (CIB) Performance Requirements

Minimum Performance Requirements for CIB Assessment					
Scenario	A1		B1	B2	C1
Target (km/h)	0		0	32	56
Vehicle (km/h)	0-50		40	72	56
Minimum Speed Reduction Requirement	No Impact At least 5/7 valid test trials	>15.8 km/h At least 5/7 valid test trials	No Impact At least 5/7 valid test trials	>15.8 km/h At least 5/7 valid test trials	>16.9 km/h At least 5/7 valid test trials

Pedestrian Automatic Emergency Braking (P-AEB) Test Results

The P-AEB analysis included a total of 19 systems ranging from MY 2016 to 2018. Similarly to the AEB evaluation, the test matrix included 4 different test scenarios (CPFA-50, CPNA-25, CPNA-75, CPNC-50) to be tested between 10 km/h and 50 km/h. The 50th percentile adult articulated pedestrian dummy was used for the first 3 scenarios mentioned, while the 7-year-old articulated child dummy was used for the CPNC-50. Unlike the AEB evaluation, the systems were not typically tested for both their CIB and DBS variants. However, two specimens which did not perform to expectations in the CIB configuration were re-tested in the DBS configuration and showed significant improvement. The speed reductions and maximum avoidance speed presented in the Tables and Figures below consist of an average of 5 out of 7 tests as previously described.

P-AEB Maximum Avoidance Speed. The maximum avoidance speeds measured during the P-AEB evaluation were seen in the CPNA-75. For this scenario, as the theoretical point of impact was past the median line of the vehicle and that there was no obstruction, it seemed easier for the systems to detect potential conflicts. Similarly to what was experienced during the AEB evaluation, some systems were challenged by speeds below 10 km/h while others were able to fully avoid a collision with a pedestrian at speeds in excess of 60 km/h. 4 of the test vehicles evaluated could not avoid a collision at any speed while 4 of them were able to avoid a collision at 50 km/h. In general, comparing the AEB and P-AEB results showed a good correlation. The top 3 performing test samples of the P-AEB evaluation are the same as the top 3 performers of the AEB evaluation.

An analysis comparing TC's results to those of Euro NCAP showed variability in 3 out of 4 sample vehicles. The speed reductions observed with TC's sample TC17-503 were higher than those measured in the Euro NCAP test for a similar model (one MY older and lower model trim). Samples TC18-020 and TC18-501 showed good correlation except for TC18-501 that could never detect a running adult in the CPFA-50 test. The previous evaluation of a different sample from the same manufacturer (TC15-509) showed the same phenomenon even if both vehicles measured up to expectations in all 3 other P-AEB test scenarios. Finally, sample TC17-512 never detected a pedestrian in any of all 4 test scenarios in TC's tests but performed well in Euro NCAP's tests.

Table 7.
TC/Euro NCAP P-AEB Maximum Avoidance Speed in km/h

	TC17-503		TC17-512		TC18-020		TC18-501	
Scenario	Euro NCAP	TC	Euro NCAP	TC	Euro NCAP	TC	Euro NCAP	TC
CPNC-50	30	40	30	No response	40	45	35	35
CPFA-50	20	50	20	No response	60	50*	50	No response
CPNA-25	40	55	35	No response	60	50*	60	50*
CPNA-75	40	60	40	No response	60	50*	60	50*

* Maximum test speed performed

P-AEB Maximum Speed Reduction. Table 8 lists the speed reductions achieved by each of the P-AEB systems in their CIB configuration. The chromatic scale previously described in the AEB section was also used to present the P-AEB results. While there was good correlation in maximum avoidance speeds between the car-to-car and pedestrian AEB results, a comparison between the two speed reduction tables clearly demonstrates that current AEB systems perform better in car-to-car scenarios than in pedestrian scenarios. This may not necessarily be a surprise as detecting moving pedestrians and predict their position in time and space is a far more complex and challenging task than detecting a larger vehicle in a straight line. Since pedestrian and vulnerable road users represent a large portion of road fatalities, this shows that P-AEB should be identified as a primary area of research where innovation and technological advancement could produce important safety improvements. The chromatic organization of the table demonstrates that the CPNA-75 scenario produced the highest speed reductions while the CPNC-50 scenario with the child dummy and obstruction had proven to be the most challenging of all scenarios. Finally, and of concerning note, the P-AEB program also demonstrated that 4 out of 19 test specimens evaluated did not provide any mitigation in any of the 4 test scenarios despite the manufacturers' claim of pedestrian avoidance capabilities.

Table 8.
Speed Reduction Provided by 19 Pedestrian AEB Systems (km/h)

Test Vehicle	CPNA-75							CPNA-25							CPFA-50							CPNC-50						
	20	25	30	35	40	45	50	20	25	30	35	40	45	50	20	25	30	35	40	45	50	20	25	30	35	40	45	50
18-020	-	-	-	-	-	-	50	20	-	-	-	-	-	50	-	-	30	-	40	-	50	20	-	30	-	40	35	28
17-503	20	-	30	-	40	-	42	17	-	30	-	40	-	49	19	-	30	-	40	41	48	-	-	-	-	38	37	27
17-504	-	-	30	-	40	-	50	20	-	30	-	40	-	50	20	-	30	-	40	-	50	-	-	30	35	24	29	33
18-501	-	-	-	-	-	-	50	20	-	30	-	40	-	50	-	-	-	-	-	-	-	-	19	-	29	35	13	-
15-509	-	-	30	-	-	-	50	10	-	30	-	38	37	-	-	-	-	-	-	-	-	20	12	-	-	-	-	-
17-010	20	-	30	-	40	38	26	19	-	30	32	21	-	-	20	25	30	35	23	26	-	-	25	8	-	-	-	-
17-509	-	-	-	-	36	21	-	20	25	14	-	-	-	-	16	23	17	-	-	-	-	20	-	25	18	-	-	-
15-501	-	-	-	-	-	37	24	1	4	-	-	-	-	-	12	12	9	-	-	-	-	10	-	-	-	-	-	-
17-505	15	-	30	29	19	-	-	7	-	-	-	-	-	-	1	-	-	-	-	-	-	-	-	-	-	-	-	-
17-506	20	-	30	14	-	-	-	13	-	-	-	-	-	-	20	21	30	12	-	-	-	20	18	13	-	-	-	-
17-508	20	21	24	-	-	-	-	11	11	-	-	-	-	-	17	15	24	-	-	-	-	18	9	-	-	-	-	-
17-507	20	25	14	-	-	-	-	5	-	-	-	-	-	-	2	-	-	-	-	-	-	-	-	-	-	-	-	-
18-014	-	-	21	-	15	-	24	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
17-501	-	-	-	26	11	-	-	8	-	-	-	-	-	-	4	-	-	-	-	-	-	1	-	-	-	-	-	-
16-504	5	-	-	-	-	-	-	13	10	18	-	-	-	-	-	-	-	-	-	-	-	1	-	-	-	-	-	-
16-001	2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
17-514	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
18-009	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
15-505	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

Fleet Averaged AEB and P-AEB Test Results. Figure 5 provides a general overview of the averaged speed reduction results observed during this study for all AEB and P-AEB scenarios in the CIB configuration, all targets combined. The intention was to provide a visual representation of the overall potential safety benefits associated with AEB and P-AEB, based on this scientific assessment. The break-down of speed reductions was in the range of: 15 km/h for pedestrian scenarios; 27 km/h for static AEB scenarios; and 43 km/h for dynamic AEB scenarios. The test to test variability is also illustrated by the error bars for each data set. The graph shows fleet average excessive braking in the range of 8-12 km/h and 4-5 km/h in the B1 and B2 scenarios, respectively, depending on the target. The red boxes represent the NHTSA performance requirements while the green box represents the requirements of the MOU between the car industry, IIHS and NHTSA, both described previously. These show that the averaged industry standard currently far exceeds the minimum performance requirements set by these two safety agencies.

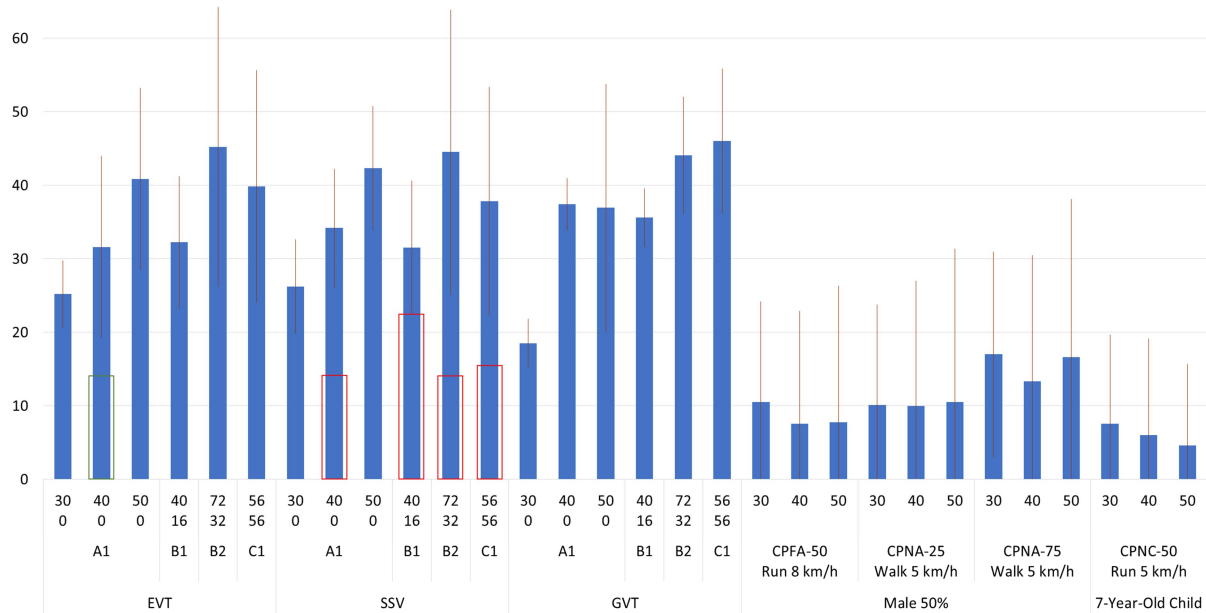


Figure 5: Averaged Speed Reductions of 36 AEB Systems and 19 P-AEB Systems (km/h)

Lane Support System (LSS) Test Results

The procedure used for the LSS evaluation was based on existing U.S. and European test protocols and was designed to capture the LSS behavior of 10 vehicles from TC's test fleet. Results from some of the test samples varied in functionalities and some systems operated differently under similar testing conditions. Some vehicles were equipped with systems that only provided warnings, while others provided warnings and correction or lane-centering capabilities. Other vehicles were equipped with LKA systems that auto-corrected without warning the driver.

Lane Departure Warning (LDW) System. All vehicles were not tested with the lane departure correction system activated. 4 out of 10 were tested in LDW only. The main focus was to evaluate the signals provided to the driver. The procedure was adapted to include the vehicles with lane correction capabilities. 4 vehicles were tested in the LDW mode and the results are presented in Table 9. 5 tests were done with the cruise control "on" in order to activate the LKA and to assist with the speed control. 3 tests were completed without cruise control. Vehicles with only the LDW functions activated resulted in at least a visual signal for all tests.

Table 9.
Lane Departure Warning

Specimen	Cruise	SSL			SDL			DC		
		Visual	Audio	Haptic	Visual	Audio	Haptic	Visual	Audio	Haptic
17-512	On	5/5	1/5	5/5	5/5	0/5	5/5	5/5	0/5	5/5
	Off	3/3	2/3	3/3	3/3	0/3	3/3	3/3	0/3	3/3
17-511	On	5/5	0/5	5/5	3/5	0/5	0/5	3/5	0/5	3/5
	Off	3/3	0/3	3/3	0/3	0/3	0/3	3/3	0/3	3/3
17-010	On	5/5	5/5	0/5	5/5	4/5	0/5	5/5	5/5	0/5
	Off	3/3	3/3	0/3	3/3	3/3	0/3	3/3	3/3	0/3
15-508	On	5/5	0/5	5/5	5/5	0/5	5/5	5/5	0/5	5/5
	Off	3/3	0/3	3/3	3/3	0/3	3/3	3/3	0/3	3/3

Lane Keeping Assist (LKA) System. Using the same tests scenarios to test the LKA functions yielded different results as can be seen in Table 10. 2 out of 8 vehicles tested stayed in their traveling lane during the 3 tests scenarios without generating warnings. This "background" system corrected for the driver to keep the vehicle in the lane and did not generated alerts unless crossing the lane. In our test, the two vehicles drove in the lane and remained between the lane markings. 4 out of 8 vehicles used their LKA system and warned the driver when approaching lane markings by using audio and visual alerts for each test. The vehicles corrected, but always warned the driver. This approach was interesting as the system tried to keep the vehicle on track, but also warned the driver if the vehicle was drifting away from the center lane. Warnings generated by number of tests are presented in the Tables below.

Table 10.
Lane Keeping Assist

Specimen	Cruise	SSL			SDL			DC		
		Visual	Audio	Haptic	Visual	Audio	Haptic	Visual	Audio	Haptic
17-503	On	On	0/5	0/5	0/5	0/5	0/5	0/5	0/5	0/5
	Off	Off	3/3	0/3	3/3	0/3	0/3	3/3	0/3	0/3
17-512	On	On	1/3	0/3	1/3	0/5	0/5	0/5	0/4	0/4
	Off	Off	0/3	0/3	0/3	0/3	0/3	0/3	0/3	0/3
18-009	On	On	5/5	0/5	0/5	5/5	0/5	0/5	5/5	0/5
	Off	Off	3/3	0/3	0/3	3/3	0/3	0/3	3/3	0/3
18-020	On	On	5/5	0/5	0/5	5/5	0/5	0/5	5/5	2/5
	Off	Off	3/3	0/3	0/3	3/3	0/3	0/3	3/3	1/3
17-010	On	On	5/5	6/5	5/5	5/5	4/5	0/5	5/5	3/3
	Off	Off	3/3	3/3	0/3	3/3	2/3	0/3	3/3	3/3
18-501	On	On	2/5	2/5	0/5	5/5	5/5	0/5	3/5	3/5
	Off	Off	0/3	0/3	0/3	3/3	3/3	0/3	2/3	2/3
17-514*	On	On	5/5	0/5	0/5	5/5	0/5	0/5	5/5	5/5
	Off	Off	3/3	0/3	0/3	3/3	0/3	0/3	3/3	3/3
17-501	On	On	5/5	5/5	0/5	4/5	4/5	0/5	1/5	1/5
	Off	Off	3/3	3/3	0/3	3/3	3/3	0/3	0/3	0/3

*LKA does not correct every time, works randomly

The other observation noted for this test is a combination of lane keeping and warning systems. 2 out of 8 vehicles produced warnings and made corrections. It was interesting to see that for consecutive and repeatable test conditions, different results were observed. One of the two vehicles had issues engaging the LKA in certain tests, resulting only in audio warnings. One vehicle did not perform the same during the SSL and SDL which could be related to lane marking quality. It could be attributed to the sensitivity to recognize the “road” like lanes or simply put, a calibration difference for this system.

For scenario #3 (S-Curve) presented in Table 11, the tests were performed starting in the right lane, moving to a dotted line first and again starting in the left lane moving towards the edge of the road first. The goal of this test was to challenge the robustness of the system in having more than 1 signal input, a left input followed by a right input. In the case of pure warning only, the driver made the correction to the steering wheel to follow the path. The length of the course was 800 meters or 40 seconds in duration. The vehicle encountered an S-shaped road with a radius of curvature of 1,219 m. Some LKA systems prompted the driver to touch the steering wheel before the end of the procedure, with the first warning appearing before the end of the course. For 26 out of 40 tests conducted, the LKA helped the driver staying in the lane and 14 out of 40 tests warned of lane departure (LDW).

Looking at all combinations of the two tests, from the right and the left lane, cruise control operational or not as well as LKA system activated, 7 out of 10 vehicles reacted the same way in terms of alerting the driver. With the LKA off, visual alerts in conjunction with a vibratory alert was produced 6 times out of 8. With the LKA on, 2 vehicles

Table 11.
Scenario #3 with LKA "off" – Warning only

Specimen	Cruise	SS			DS		
		Visual	Audio	Haptic	Visual	Audio	Haptic
15-508	On	5/5	0/5	5/5	5/5	0/5	5/5
	Off	3/3	0/3	3/3	3/3	0/3	3/3
17-514	On	5/5	0/5	0/5	5/5	0/5	0/5
	Off	3/3	0/3	0/3	3/3	0/3	0/3
17-503	Off	3/3	0/3	3/3	0/3	0/3	3/3
17-512	On	5/5	4/5	5/5	5/5	0/5	5/5
	Off	3/3	3/3	3/3	3/3	0/3	3/3
17-511	On	5/5	0/5	5/5	5/5	0/5	5/5
	Off	3/3	0/3	3/3	3/3	0/3	3/3

Table 12.
Scenario #3 with LKA activated

Specimen	Cruise	SS			DS		
		Visual	Audio	Haptic	Visual	Audio	Haptic
17-514	On	0/5	0/5	0/5	5/5	0/5	0/5
	Off	0/3	0/3	0/3	3/3	0/3	0/3
18-501	On	5/5	5/5	0/5	2/5	2/5	0/5
	Off	3/3	3/3	0/3	3/3	3/3	3/3
17-010	On	5/5	5/5	0/5	5/5	5/5	0/5
	Off	3/3	3/3	0/3	3/3	3/3	0/3
17-503	On	0/5	0/5	0/5	4/5	1/5	0/5
17-512	On	0/3	0/3	0/3	0/3	0/3	0/3
	Off	0/2	0/2	0/2	0/3	0/3	0/3
18-009	On	5/5	0/5	0/5	5/5	0/5	0/5
	Off	3/3	0/3	0/3	3/3	0/3	0/3
18-020	On	5/5	0/5	0/5	5/5	0/5	0/5
	Off	3/3	0/3	0/3	3/3	0/3	0/3
17-501	On	5/5	5/5	0/5	3/5	3/5	0/5
	Off	3/3	3/3	0/3	3/3	3/3	0/3

out of 6 warned the driver with both a visual and audible signal. 3 vehicles only warned visually and 1 vehicle did not warn the driver and simply maintained its lane for the duration of the test. Two vehicles were not consistent with their warnings while the LKA was engaged and the number of alerts varied depending on whether the test was performed from a dotted line to a solid lane and vice-versa.

A difference in system reaction was observed during scenario #3, a test that represented real road conditions. It was interesting to capture the limits of the system under more challenging situations. Table 11 showed warning only and Table 12 with LKA activated mode during scenario #3.

DISCUSSION

The specific objectives of this study were as follows: evaluate the performance of ADAS to determine their potential in reducing fatalities and injuries on Canadian roadways; determine the limitations of ADAS to identify potential risks to road safety; provide scientific evidence to help shape future regulatory, research and policy development surrounding automated and connected vehicle technologies; assess and develop test methods and procedures; and evaluate the suitability of surrogate vehicle and pedestrian targets for future research and regulatory programs. To address these objectives, 7,710 individual crash avoidance tests obtained from 36 ADAS-equipped vehicles were conducted at the MVTC. While the effects of all test parameters are included in this discussion, the focus of the study banks on results obtained on-track and in standard conditions. An in-depth analysis of these results follows.

AEB. AEB systems were evaluated for their CIB and DBS variants according to 4 different test scenarios with 3 different targets replicating the characteristics of a real vehicle. The test results suggested that all systems were not designed equally. Important performance variability were observed across the fleet and some systems were not even capable of avoiding collisions in static scenarios. However, when comparing results against established performance criteria set forth by internationally recognized road safety organizations, 24 out of 36 AEB systems achieved a fully satisfactory level of performance. Concurrently, only 2 of the systems did not meet the minimum performance requirement used for the voluntary MOU signed between IIHS, NHTSA and the car industry for a commitment to make AEB a standard feature by 2022 in the U.S.

Overall, the evaluation of the CIB and DBS variant of the systems did produce similar results but for a few specimens, the level of performance measured in the DBS configuration far exceeded the level of performance measured in the CIB configuration. For instance, one of 2 vehicles that could not avoid a rear-end collision at any speed in the CIB configuration was able to avoid a collision at 50 km/h in the DBS configuration. The maximum avoidance speed measured for each of the test vehicles was found to be mostly target dependent. While 11 test specimens produced the same results independently of which target they were evaluated with, 15 vehicles could avoid the target at a higher speeds when tested with the EVT target.

A chromatic scale of the results obtained during the AEB evaluation was developed to provide an overall visual perspective of what can be expected from AEB technology in terms of safety benefits as its deployment in the field is in constant progression. The chart created clearly demonstrates that AEB technology can provide significant improvements in terms of collision mitigation which can directly result in reduced road casualties.

P-AEB. 19 P-AEB systems were evaluated according to 4 different test scenarios simulating some of the most common real-life situation involving collision between vehicle and adult or child pedestrians. The maximum avoidance speeds of the P-AEB evaluation were observed for the CPNA-75 condition. For this scenario, as the theoretical point of impact was past the median line of the vehicle and that there was no obstruction, it seemed easier for the systems to detect potential conflicts. Similarly to what was experienced during the AEB evaluation, some systems were challenged at speeds below 10 km/h while others were able to fully avoid a collision with a pedestrian at speeds in excess of 60 km/h. Overall, the speed reductions observed during the AEB evaluation of the systems were more important than those observed during the P-AEB evaluation. This may not necessarily be a surprise as detecting moving pedestrians and predict their position in time and space is a far more complex and challenging task than detecting a larger vehicle in a straight line.

An analysis comparing TC's results to those of Euro NCAP showed variability in 3 out of 4 sample vehicles. It also showed that one of the sample vehicle never detected a pedestrian in any of all 4 test scenarios in TC's tests while it performed well in the Euro NCAP tests.

Finally, and of concerning note, the P-AEB testing program demonstrated that 4 out of 19 test specimens did not provide any mitigation in any of the 4 test scenarios despite the manufacturers' claim of pedestrian detection capabilities. Since vulnerable road users and more specifically pedestrians account for a large portion of road fatalities, this shows that P-AEB should be identified as a primary area of research where innovation and technological advancement could produce important safety improvements.

LSS. As more advanced LSS testing methods are being developed using steering robots, such as described in the *Euro NCAP Lane Support Systems* test protocol [10], the testing procedure developed for this program demonstrated some limitations. The work presented here consists of an exploratory approach aiming at evaluating the status of commercially available LSS under realistic conditions. The operational limitations of 10 LSS systems were evaluated on a mixture of roads at the MVTC according to 3 different scenarios.

4 out of 4 vehicles tested with LDW produced visual warnings for SSL, SDL and DC. For that same sequence, 1 vehicle constantly produced visual and audio warnings while the others generated a combination of visual and haptic or visual and audio warnings. Only 1 vehicle generated haptic, audio and visual warnings for the SS test only. With LKA activated, 2 out of 8 vehicles stayed on their traveling lane for the SSL, SDL and DC scenarios without generating warnings. The system operated in the background and did not communicate with the driver. 3 out of 8 vehicles generated audio and visual alerts. The SS scenario was more consistent than the DS scenario as only 2 vehicles reacted differently from SS and DS. Scenario #3 was performed only with LKA activated and simulated real-world driving of an S-Curve. Only one vehicle generated a haptic signal during the DS test with the cruise control "off". This test was more challenging as 4 out of 8 vehicles did not reproduce the same warnings going into the SS or DS test. It may be attributed to lane markings as differences with respect to line types were observed in other scenarios. LSS was only constant for visual warnings and not for the enhancement of haptic and audio signals.

While the preferred strategy used to warn drivers of lane crossing for the systems tested during this evaluation was through visual signals, supplemental haptic and audio signals were inconsistent from vehicle to vehicle. At times, test drivers felt bombarded with alarms and signals without exactly knowing how they should be interpreted. System sensitivity to lane markings also seemed to be an issue for a subset of sample test vehicles. Ideally, more data and a comprehensive human factor assessment would be required in order to articulate an accurate estimate of potential safety benefits associated with LSS technologies.

Findings. As the deployment of ADAS is in constant progression, TC will continue to monitor the evolution and performance of new systems introduced on the global markets. As mentioned previously, despite being in its relative infancy, ADAS safety benefits are already recognized by several international consumers, insurance and safety organizations [2] [3]. Results from this study clearly demonstrated that AEB and P-AEB technologies can provide significant improvements in terms of collision mitigation which can directly result in reduction of road fatalities and injuries. An in-depth analysis of these results showed that while driving at speeds typical of an urban environment, the vehicle fleet evaluated in this study could provide average speed reductions of: 15 km/h in pedestrian scenarios; 27 km/h in static scenarios; and 43 km/h in dynamic scenarios. Furthermore, 66% of all tests conducted during the AEB evaluation resulted in a full avoidance. While it is not expected that such a ratio would translate to real-world conditions it seems that the findings of this study are in line with those of other studies that predicted that AEB technology could potentially reduce rear-end collisions by 38% to 50% [14] [15].

Some limitations of AEB and P-AEB systems were also exposed during this evaluation. While most systems demonstrated a satisfactory level of performance when compared against established performance criteria, the overall results suggested important performance variability across the entire fleet. Scenarios replicating AEB activation in moving traffic showed that excessive braking was generated by most systems. While the speed reduction required for the *fast vehicle approaching a slow vehicle* scenarios should ideally match the speed of the vehicle ahead and not crash into it (i.e., 16 km/h and 32 km/h), most of the test specimens rather came to a full stop. This represented speed reductions of 40 km/h and 72 km/h, respectively. This excessive deceleration is concerning as it shows a situation where AEB systems could generate higher safety risks than those they can prevent in high

density traffic. Only a few of the latest, pricier and more technologically advanced specimens behaved appropriately in these tests. Of equally concerning nature, 4 out of 19 vehicles evaluated for P-AEB were never able to avoid a collision with a pedestrian.

While a full analysis on the effects of weather conditions on AEB and P-AEB as not yet been completed due to insufficient data, it is worth mentioning that decreased performance was observed in both rain and winter conditions. More data is also required in order to articulate a comprehensive assessment of LSS technologies and their associated safety benefits due to variability in test results and generalized unpredictable system behavior.

CONCLUSION

The concept of mitigating the severity of a collision or avoiding it altogether being the best possible way to reduce traffic-related fatalities and injuries on motorways is certainly something that resonates well with most motorists. Modern ADAS technologies hold the promise of doing just that. They could potentially, or will, save thousands of lives around the world in years to come while we await a driverless and collision free future. This is assuming that they are used within the scope of their limitations and functionalities, and that it is understood that for the time being, in the vast majority of situations, they are only designed to assist drivers and not replace them.

Since its inception, TC's crash avoidance program has been investigating some of the most prominent ADAS technologies currently available on the market and evaluating how they can benefit Canadians. Results from this study clearly demonstrated that AEB and P-AEB technologies can provide significant improvements in terms of collision mitigation which can directly result in reduced road fatalities and injuries. These findings are also in line with those of studies based on real-World data predicting significant reductions in rear-end collisions due to AEB deployment.

Nonetheless, this research program also exposed an important number of flaws and performance variability. While the best AEB and P-AEB systems were able to fully avoid collisions with vehicles and pedestrians at speeds up to 60 km/h, others were challenged at speeds below 10 km/h. A few P-AEB systems were never able to avoid a collision with a pedestrian despite manufacturers' claims of pedestrian detection capabilities. Scenarios replicating AEB activation in moving traffic showed that most systems unnecessarily came to a full stop rather than match the speed of vehicles they detected on their path, potentially generating higher safety concerns than those they were designed to prevent. Finally, due to variability in test results and general unpredictable system behaviour, it was not possible to gather enough data to confidently assess the potential safety benefits associated with LSS.

AEB, P-AEB and LSS are essential components of automated driving systems which will need to reliably brake and steer at all time to safely avoid other road users. That level of performance is not yet evident from the extensive testing carried out within this project. Substantial progress is therefore needed to reach the level of detection, braking and steering performance that will be required to make commercial automated driving systems a reality.

ACKNOWLEDGMENTS

Motor Vehicle Safety (TC), Human Factors (TC), ecoTECHNOLOGIE for Vehicles (TC), Compliance (TC), Collision Investigations (TC), Defects and Recalls (TC), Transportation Division (ECCC), Emissions Research and Measurements Section (ECCC), PMG Technologies, Volvo Canada

DISCLAIMER

The contents of this report reflect the views and interpretation of the authors, who are responsible for the results, the information, and their accuracies herein. The contents do not necessarily represent, or otherwise reflect, the official opinion, position or policies of Transport Canada or the Government of Canada.

REFERENCES

- [1] Transport Canada, "National Collision Database," Transport Canada, Ottawa, 2017.
- [2] NHTSA, "New Car Assessment Program," Federal Register, Washington DC, 2015.
- [3] Thatcham Research, "What is AEB?," 2019. [Online]. Available: <https://www.thatcham.org/what-we-do/car-safety/autonomous-emergency-braking/>. [Accessed March 2019].
- [4] NHTSA, "Crash Imminent Brake System Performance Evaluation for the New Car Assessment Program," Washington DC, 2015.
- [5] NHTSA, "Dynamic Brake Support Performance Evaluation Confirmation for the New Car Assessment Program," Washington DC, 2015.
- [6] ISO TC 204/WG14 N309.48, "Intelligent Transport Systems - Forward Vehicle Collision Mitigation Systems - Operation, Performance, and Verification Requirements," 2012.
- [7] ISO/FDIS 11270:2014(E) , "Intelligent transport systems lane keeping assistance systems (LKAS) performance requirement and test procedures," 2014.
- [8] Euro NCAP, "AEB Systems (Car-to-Car)," 2017.
- [9] Euro NCAP, "AEB Systems (Vulnerable Road Users)," 2017.
- [10] Euro NCAP, "Lane Support Systems," 2017.
- [11] IIHS, "Autonomous Emergency Braking Test Protocol (Version 1)," Insurance Institute for Highway Safety, Ruckersville, VA, 2013.
- [12] IIHS, "Pedestrian Autonomous Emergency Braking Test Protocol (Version 1)," Insurance Institute for Highway Safety, Ruckersdale, VA, 2018.
- [13] Central Intelligence Agency, "The World Factbook - North America - Canada," [Online]. Available: <https://www.cia.gov/library/publications/resources/the-world-factbook/geos/ca.html>. [Accessed March 2019].
- [14] Fildes, "Effectiveness of low speed autonomous emergency braking in real world rear-end crashes," Accident Analysis and Prevention, Melbourne, 2015.
- [15] J. B. Cicchino, "Effectiveness of forward collision warning and autonomous emergency braking systems in reducing front-to-rear crash rates," Accident Analysis and Prevention, 2017.
- [16] NHTSA, "Lane Departure Warning System Confirmation Test and Lane Keeping Support Performance Documentation," Washington DC, 2013.

AMOK SAFETY LOCK (ASL)

DEVELOPMENT AND DEMONSTRATION OF A NEW FUNCTION FOR THE PREVENTION OF INTENTIONAL VEHICLE MISUSE AGAINST PEDESTRIANS

João Graciano, Miso Kvesic, Thorsten Scheibe, Dr.-Ing. Dominik Kufer, Dr. Roland Kallweit

IAV GmbH Ingenieurgesellschaft Auto und Verkehr
Carnotstraße 1
10587 Berlin
Germany

Paper Number 19-0317

ABSTRACT

Most fatalities and serious injuries in traffic result from accidents caused by human error. Today, a series of driver assistance functions exist to help avoid or reduce the severity of such accidents (e.g. Autonomous Emergency Braking), while still allowing the driver to interrupt the function at any time. This overriding behavior – mandated by the Wiener convention [1] – is particularly important in the case of an incorrect function activation on the part of the vehicle's system. Due to this built-in override functionality, driver assistance functions – which typically support the driver in de-escalating a critical situation – cannot help preventing cases where drivers actively target pedestrians with the vehicle (as in recent vehicle ramming attacks). This makes clear the need for active safety functions able to prevent the driver from (intentionally or unintentionally) causing harm to other traffic elements. The function Amok Safety Lock (ASL) was developed as a prototype function to research the possibility of increasing the safety of pedestrians in the case of vehicle misuse. The function ASL looks at the driver's driving behavior, the predicted vehicle's motion and the relative positions and motions of pedestrians in the vicinity of the vehicle to identify an imminent collision. If the driver does not act to de-escalate the situation, the function initiates an emergency braking maneuver without the possibility of overriding. Simultaneously, warning signals (horn, front and turn lights) are emitted to alarm the pedestrians nearby. This behavior was confirmed in both simulations and vehicle tests using IAV's Vehicle-in-the-Loop approach. Due to its unilateral behavior, changes in the legal framework are necessary before such a function can be deployed.

INTRODUCTION

Motivation

Advanced Driver Assistance Systems (ADAS) are a key feature of modern vehicles and have contributed to a significant reduction in traffic accidents and traffic-related deaths [2]. One such function is the Autonomous Emergency Braking (AEB), nowadays available for most light and heavy vehicles: it uses environment information gathered by sensors to identify an immediate collision with another traffic element and, if the driver is unresponsive, activates an emergency braking maneuver and relevant safety systems (e.g. safety belt). Due to regulations put in place at both international [1] and national level [3], all ADAS functions are required to allow an override by the driver at any time. Due to this override capability, ADAS-functions are incapable of preventing drivers from causing injuries to other traffic elements (of which pedestrians are the most vulnerable), as demonstrated by the numerous terrorist attacks which saw drivers intentionally targeting pedestrians with vehicles [4]. To prevent such cases a function is necessary that takes control *away* from the driver, a requirement that clashes directly with the need for the permanent possibility of an override.

To bridge these two conflicting requirements and at the same time contribute to the discussion over regulations for advanced driver assistance functions, a new active safety function Amok Safety Lock (ASL) was developed at IAV GmbH, which can unilaterally trigger an emergency maneuver if the driver intention is recognized as nefarious.

Scenarios

The recent cases of terrorist ramming attacks [4, 9] provide some hints for defining the functional range of the ASL function and therefore to identify the relevant scenarios. Approximately 86% of the fatalities happened in public streets or public gatherings [9]; in all situations, the driver intentionally accelerated while steering to target pedestrians; and it continued to do so even after a first collision (that is, it was not a one-off situation). With these characteristics in mind, a representative scenario was developed and used as reference for the demonstration of the ASL functionality (see Figure 1. The reference scenario for the Amok Safety Lock function: the vehicle leaves the road and targets pedestrians). In this scenario, the driver steers the vehicle outside of the road and targets pedestrians. Taking this scenario as reference, several scenario variations were developed to validate the function's behavior. In these scenarios, the following characteristics were varied and combined:

- On-road vs. off-road
- Driver steering and acceleration/braking behavior
- Avoiding vs. targeting behavior
- Parking speed vs. attack speed
- Relative position of other pedestrians (avoidance maneuver available vs. not available)
- Prediction of pedestrian motion (static vs. dynamic)



Figure 1. The reference scenario for the Amok Safety Lock function: the vehicle leaves the road and targets pedestrians

FUNCTIONAL ARCHITECTURE

The functional range of the ASL function was initially divided into four high-level requirements:

- a) The driver intention shall be estimated;
- b) Potential collisions with pedestrians shall be predicted;
- c) Potential collision avoidance maneuvers shall be identified;
- d) If the driver's intention is estimated as nefarious (no de-escalation of the situation) and an unavoidable collision with at least one pedestrian is identified (i.e. no collision avoidance maneuvers available), the ASL function shall bring the vehicle into a safe state and trigger warnings to the immediate surroundings, without the possibility of an override by the driver.

The functional architecture of the ASL function closely follows this breakdown and was implemented as illustrated in Figure 2. System overview and main functional blocks of the ASL function. All the functional blocks are executed in real-time such that, should the conditions change, the function can immediately react.

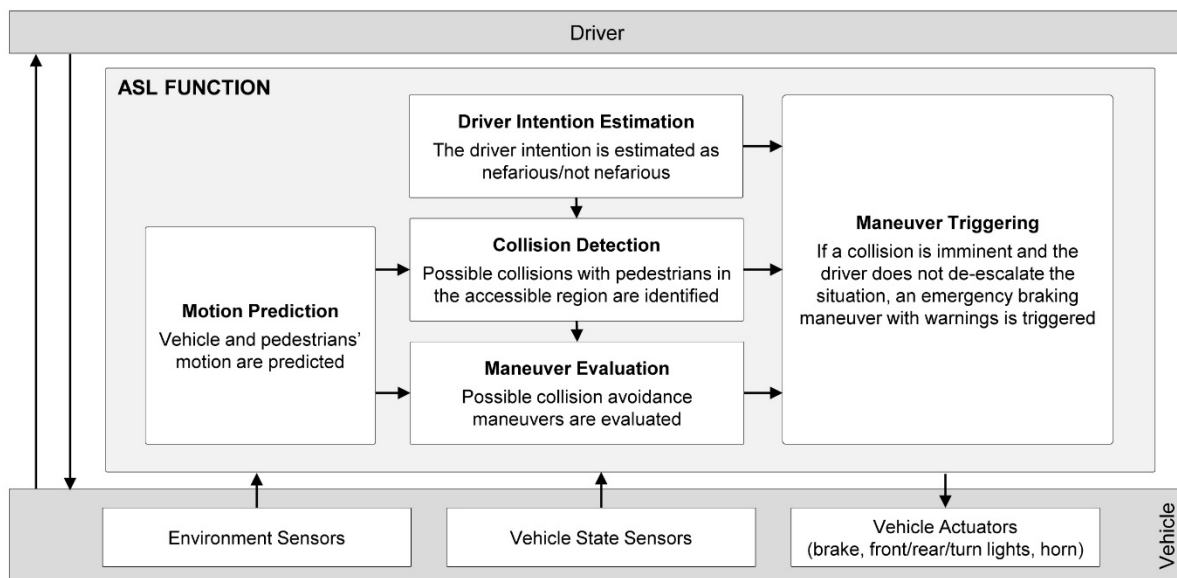


Figure 2. System overview and main functional blocks of the ASL function

Estimation of driver intention

A driver typically de-escalates a dangerous collision situation by braking and/or steering the vehicle away from the collision. To estimate the driver's intention ('requirement a' above), the ASL function monitors the gas and brake pedals, and the steering wheel. The driver's intention is classified as "nefarious" if the driver does not steer the vehicle away from pedestrians and/or does not reduce speed (i.e. does not press the brake pedal). If the driver does act to avoid the collision, no triggering of the emergency braking maneuver takes place, even if his actions are evaluated as insufficient to completely avoid the collision.

To further support the estimation of the driver's intention and minimize the probability of an unjustified ASL triggering (particularly important considering the significant impairment the ASL causes to the driver), two additional criteria are taken into account:

- Information about the road limits (road marks, curb, high-precision positioning) is used to determine if the vehicle is driving *on* or *outside* the road. The ASL function is allowed to trigger a collision avoidance maneuver only after the vehicle leaves the road (vehicle state changes from in- to off-road);
- The vehicle's speed is used to limit the ASL activation: an emergency maneuver can be triggered only if the speed is within a given range (currently 10 km/h – 80 km/h). This helps eliminating cases where the vehicle moves very slowly and accidentally touches a pedestrian (e.g. vehicle driving slowly through a crowd) and general cases where damages are expected to be minor.

Motion prediction

For the prediction of the pedestrians' motion, and due to the relatively short time-scales involved in typical collision-scenarios (milliseconds to a few seconds), a relatively simple motion model assuming constant speed was used (more complex models are possible [8]). To predict the vehicle's motion the ASL function uses a clothoid-based approach which takes into account vehicle-specific dynamical characteristics to generate a realistic dynamical motion for the particular vehicle [5].

The prediction calculation identifies three relevant regions in the environment around the vehicle (Figure 3. The vehicle's surrounding region is divided into three regions with different criticality.):

- Region 1 – The »most critical« region, which will be driven through with certainty, independently of changes made to the vehicle dynamics;
- Region 2 – The »critical« region, which will be driven through with certainty if the vehicle holds its current state;
- Region 3 – The »latent critical« region, which could be reached if the vehicle changes its current motion.

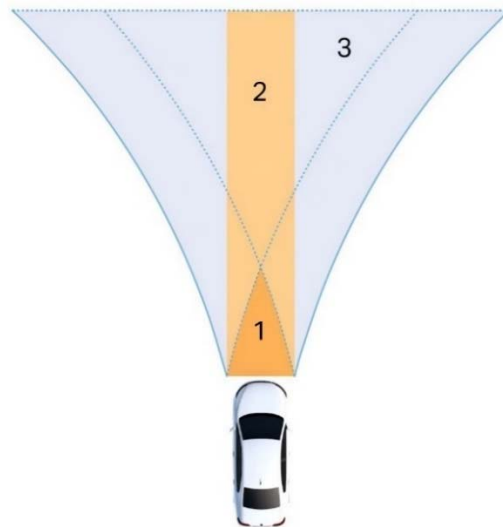


Figure 3. The vehicle's surrounding region is divided into three regions with different criticality.

Region 3 is used to identify all relevant pedestrians - pedestrians which are detected by the sensors outside this region are not considered. Region 2 is used to estimate potential collisions if the driver does not change the current vehicle's motion. Region 1 is used to trigger the emergency braking maneuver: the limits of this region represent the last possible moment at which a collision avoidance maneuver can be successfully undertaken by the driver.

Collision detection

The identification of a collision with pedestrians ('requirement b') is performed by calculating the intersection of the area swiped by the vehicle during its predicted motion with the area covered by the pedestrian during its predicted motion. Additionally, a distinction is made between an individual pedestrian and a group of pedestrians: if the distance between pedestrians is less than a given threshold (taken as the approximate width of the vehicle), they are considered to be a "group". This group classification is then used in the next step to identify possible collision avoidance trajectories for the vehicle (i.e. trajectories which lead the vehicle between groups).

Maneuver evaluation

After identifying all possible collisions with pedestrians, the ASL function searches for maneuvers which can avoid the predicted collision (requirement c). To identify an unavoidable collision, the function executes sequentially the following steps (Figure 4. The steps for identification of a collision-free vehicle path (for simplicity the motion of pedestrians is not represented). From left to right: a pedestrian is identified in the vehicle's path; other pedestrians are identified in the accessible region; a collision-avoidance path between groups of pedestrians is determined.):

1. The function determines the predicted presence of at least one pedestrian in the »critical« area (zone 2 in Figure 3). If there are several pedestrians in the critical area, the one closest to the vehicle is taken as reference;
2. The function detects other pedestrians in the »latent critical« area (zone 3 in Figure 3) and separates all pedestrians into groups with at least one pedestrian;
3. The function verifies the existence of trajectories capable of leading the vehicle between the groups of pedestrians without colliding with any of them. Any other objects detected in the vicinity of the vehicle are also considered in this step.

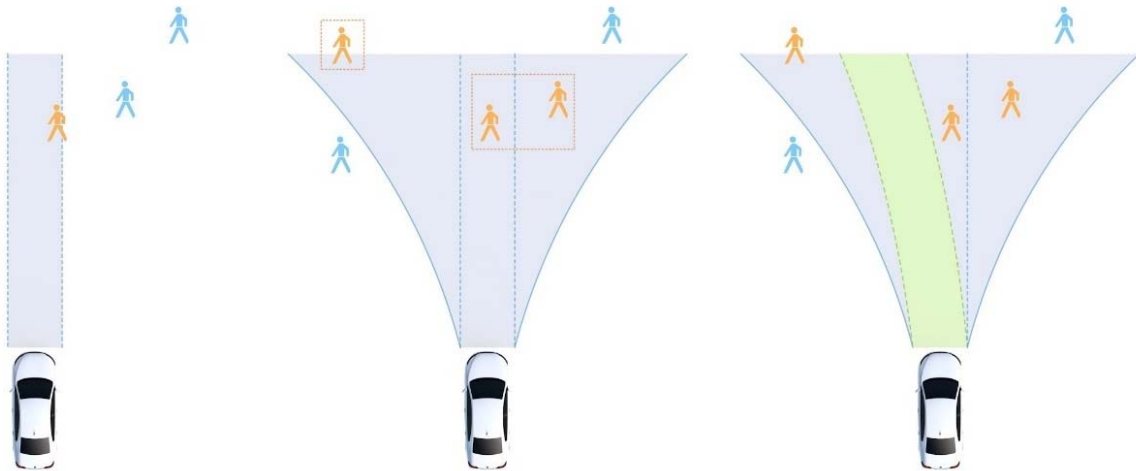


Figure 4. The steps for identification of a collision-free vehicle path (for simplicity the motion of pedestrians is not represented). From left to right: a pedestrian is identified in the vehicle's path; other pedestrians are identified in the accessible region; a collision-avoidance path between groups of pedestrians is determined.

If no collision-free maneuver exists at end of step 3, the collision is classified as unavoidable (more exactly: the collision becomes classified as unavoidable shortly before it becomes unavoidable, as to provide sufficient reaction time for the system). As long as no pedestrian is predicted to be in the critical area (step 1) or at least one collision-free maneuver exists (step 3), the function will not perform any action and will not trigger an emergency braking.

Maneuver triggering

If a collision with a pedestrian is imminent (i.e. the vehicle is about to enter a state where no collision avoidance maneuver is feasible) and the driver does not de-escalate the situation (i.e. does not brake or steer away from collision), the function ASL triggers an emergency braking maneuver without the possibility of driver intervention, effectively bringing the vehicle to a standstill ('requirement d'). Additionally, acoustic (horn) and optical (front, rear and turn lights) warnings are triggered to warn the immediate surroundings about the dangerous driver's behavior.

VALIDATION

The ASL function was validated concurrently using computer simulations and vehicle tests. While simulations allowed for the exact verification of the function's logic, the validation in a real vehicle allowed the function to achieve a high degree of maturity in a relatively short period of time. This was possible by using IAV's Vehicle-in-the-Loop test approach [6, 7]. In this test method, a real vehicle is fed with virtual traffic objects (in this case pedestrians and roads); virtual sensors then detect the (also virtual) objects and pass this information to the ASL function which, if necessary, commands the (real) actuators to act. The function itself does not run on the vehicle's target hardware but on a standard laptop computer while the tester can observe the scene as seen from the driver's point-of-view in a display fixed to the windscreen (see Figure 5. Inside IAV's Vehicle-in-the-Loop: the test scenario is visualized in a display showing the (real) environment and the (virtual) pedestrians.). The use of this setup allowed to test the ASL function in all developed scenario variations using relatively little resources and without endangering any pedestrians.



Figure 5. Inside IAV's Vehicle-in-the-Loop: the test scenario is visualized in a display showing the (real) environment and the (virtual) pedestrians.

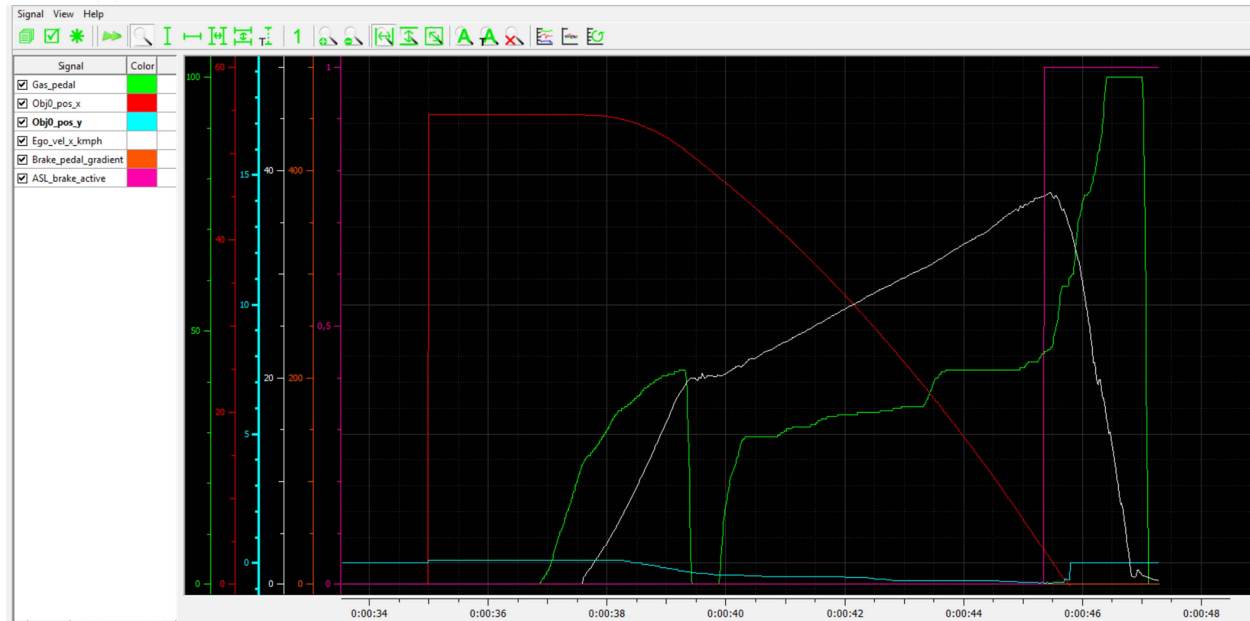


Figure 6. Validation of the ASL function using IAV’s Vehicle-in-the-Loop approach: the vehicle breaks until standstill (left) and simultaneously activates lights and horn (right) even if the driver tries to accelerate.

A particular important part of the validation was the verification of the function’s full authority, i.e. the demonstration that control over the acceleration of the vehicle was taken *away* from the driver. In Figure 6. Validation of the ASL function using IAV’s Vehicle-in-the-Loop approach: the vehicle breaks until standstill (left) and simultaneously activates lights and horn (right) even if the driver tries to accelerate. are shown the results of such a test case. At first, the driver accelerates (signal “Gas_pedal”) and continuously reduces the distance to the pedestrian (signals “Obj0_pos_x” and “Obj0_pos_y”). Once the collision becomes imminent, the ASL function requests a braking maneuver (signal “ASL_brake_active”). Despite the driver accelerating (note that the brake pedal is not pressed, see signal “Brake_pedal_gradient”), the vehicle slows down to standstill (consequently the engine stalls and shuts down).

CONCLUSIONS

There have been approximately 78 terrorism-motivated vehicle ramming attacks between 1973 and 2018, from which resulted 281 deaths and approximately 1200 injuries [9]. Even if the number of casualties is not comparable with the casualties due to other causes, the psychological effects on the society at large are significant. The possibility to actively influence the motion of a vehicle opens up possibilities for increasing the safety of pedestrians in addition to the safety of the vehicle’s occupants. Particularly in the case of an intentional misuse of a vehicle it is important to have functionalities capable of avoiding or at least minimise the harm to pedestrians, i.e. some kind of “driver prevention” functionality.

The ASL function monitors the driver’s behavior (steering wheel, brake and acceleration pedals) and the environment. If an imminent collision with a pedestrian is identified and the driver does not maneuver to avoid the collision, the function commands an emergency braking maneuver until the vehicle is brought to a standstill and activates optical (front and turn lights) and acoustical (horn) warnings to the surroundings. Once the emergency braking is activated, the function cannot be overridden by the driver: the vehicle is brought to standstill and warnings are emitted, even if the driver tries to accelerate or maneuver. Tests using IAV’s Vehicle-in-the-Loop approach have demonstrated the correct functioning of the ASL: in the case of an imminent collision, the function

activates and brings a real vehicle to standstill even if the driver accelerates, while activating the acoustic and optical warnings. Furthermore, the use of simulations and Vehicle-in-the-Loop testing back-to-back allowed the function to reach a high maturity level in a short timeframe: while simulations confirmed the correct logic of the function, Vehicle-in-the-Loop tests demonstrated its robustness vis-à-vis the inputs from the vehicle, i.e. the real vehicle dynamics. Because of the nature of the test approach, issues specific to sensors and sensor measurements (e.g. faulty sensor data) were largely not addressed but need to be before such functions can be deployed. With the objective of increasing the ASL function's robustness, several new approaches are currently being evaluated, including new motion models [8] and new methods for determining the vehicle's position relative to the road (e.g. artificial intelligence for curb recognition).

The function ASL is not meant as substitute to existing Autonomous Emergency Braking functions, but as an extension thereof; and while its functionality clearly goes against current vehicle regulations [1, 3], it is also a case in point on how to increase function autonomy while contributing to further reduce the number of casualties caused by (intentional or unintentional) human action. However, changes in regulations are needed before such functionalities are implemented.

Currently, every ADAS function is required to allow an overriding [10]. While this is intended to allow the driver to perform his duties according to road traffic legislation, it does nothing to prevent the driver from going against that same legislation. Legislation is currently being drafted to allow autonomous systems to drive but not to let them *prevent* the human from driving. To effectively give control of a vehicle to the machine instead the human sitting in the driver's seat, both the circumstances in which this can happen as well as the actions allowed to happen have to be very clearly defined. With that in mind, the following regulatory changes could help the deployment of this functionality:

- Definition of the range of vehicle states. Only when the vehicle is in a specific state should any function be allowed to have full authority over any aspect of the vehicle control. The most immediate one is the state where all the necessary sensors are operational. But other ones are possible (e.g. only when no trailer is present), and these should be explicitly laid out;
- Definition of the range of actions. Any function preventing a human user from exerting control over the vehicle shall be allowed to have full authority over only very specific dynamic tasks. In a first step, this influence could extend to longitudinal control and more specifically to deceleration; in a further step, the function could be allowed to also perform lateral control;
- Definition of the range of circumstances. As implemented into the ASL function, full authority over the vehicle (even if just a specific action) should be allowed only in very strict circumstances. These circumstances should be highly critical and explicitly connected with danger to human life in the immediate vicinity of the vehicle.

Apart from these regulatory changes, technical developments are also necessary, especially what concern the certification mechanism for such functions. As it is currently being discussed in the framework of autonomous driving, the current test process should be updated for dealing with the extreme requirements of such a function. Once the test process is accepted at the regulatory and legal level, the question of liability is automatically addressed.

We thank Paul Prescher, Steve Haselbach, Anton Egger and Matthias Butenuth for their support and motivation.

REFERENCES

- [1] (1968) Article 8, 19th Convention on Road Traffic, United Nations, Vienna, 8 November
- [2] J. Cicchino (2017) “Effectiveness of Forward Collision Warning Systems with and without Autonomous Emergency Braking in Reducing Police-Reported Crash Rates”, Insurance Institute for Highway Safety, January
- [3] (in german) Straßenverkehrsgesetz (2019) “§1a Kraftfahrzeuge mit hoch- oder vollautomatisierter Fahrfunktion”
- [4] (2019) “Vehicles as Weapons of Terror”, Counter Extremism Project, January (available online at https://www.counterextremism.com/sites/default/files/Vehicles%20as%20Weapons%20of%20Terror_010819.pdf)
- [5] (in german) M. Kvesic (2018) “Trajektorienplanung für hochdynamisches autonomes Fahren”, Master Thesis, Hochschule für angewandte Wissenschaften München
- [6] M. Butenuth, R. Kallweit and P. Prescher (2017) „Vehicle-in-the-Loop – Combining real vehicle tests with virtual scenes“, in ATZ - Automobiltechnische Zeitschrift, 09
- [7] R. Kallweit, P. Prescher, and M. Butenuth (2017) „Vehicle-in-the-loop: augmenting real-world driving tests with virtual scenarios in order to enhance validation of active safety systems“, in Proceedings of the 25th International Technical Conference on the Enhanced Safety of Vehicles
- [8] (in german) F. Pinsker, K. Krumbiegel and J. Graciano (2019) “Analytisches und numerisches Verfahren zur Prädiktion eines beweglichen Verkehrsteilnehmers” (patent pending)
- [9] B. Jenkins and B. Butterworth (2018) “An Analysis of Vehicle Ramming as a Terrorist Tactic”, MINETA Transportation Institute, May (available online at transweb.sjsu.edu/sites/default/files/SP0518%20Vehicle%20Ramming%20Terrorism.pdf)
- [10] (2008) “Regulation No 79 of the Economic Commission for Europe of the United Nations (UN/ECE) - Uniform provisions concerning the approval of vehicles with regard to steering equipment”, Addendum 78: Regulation No 79, Revision 2, 27.05 (available online at eur-lex.europa.eu/legal-content/en/ALL/?uri=CELEX%3A42008X0527%2801%29)

APPROACH FOR DERIVING SCENARIOS FOR SAFETY OF THE INTENDED FUNCTIONALITY

Paul Rau

National Highway Traffic Safety Administration
United States

Christopher Becker

John Brewer

Volpe National Transportation Systems Center, USA

Paper Number 19-0258

ABSTRACT

Safety of the Intended Functionality (SOTIF) is a safety process in the automotive industry that addresses unintended system behaviors in the absence of electronic faults. Electronic system malfunctions are addressed through industry's functional safety process, ISO 26262. SOTIF on the other hand helps mitigate hazards that may arise when the driving conditions exceed the technology limitations of one or more system components or from certain human factor considerations, such as foreseeable system misuse or mode confusion.

The current approach applies a combination of analysis, simulation, test track, and on-road testing to identify unknown and potentially unsafe scenarios. This study supports the analytical part of this approach by developing a structured framework for deriving scenarios necessary for a SOTIF analysis. The scenarios derived through this framework could then be used to inform simulation and testing.

This paper provides a brief overview of the SOTIF process, describes the development of a framework for deriving scenarios, and presents preliminary results from applying this framework to a highly automated chauffeur system. The framework described in this paper could evolve over time as additional SOTIF-relevant parameters are identified.

INTRODUCTION

Driving automation systems and other advanced electronic and electrical (E/E) systems have the potential to transform the transportation landscape. Safety assurance of E/E systems introduced into the vehicle fleet is a primary consideration for industry and regulators. Recognizing the unique safety challenges presented by E/E systems, such as heavy reliance on software and complex system interactions, the International Organization for Standardization (ISO) published ISO 26262 (Functional Safety – Road Vehicles). ISO 26262 represents the current approach in the automotive industry with respect to the functional safety of E/E systems [1].

Functional safety deals primarily with electronic faults in E/E systems and is one component of the overall evaluation of system safety. In 2019, ISO published Publicly Available Specification (PAS) 21448 (Safety of the Intended Functionality; SOTIF). SOTIF is a complementary process to functional safety that addresses the identification and mitigation of hazardous events that may occur in the absence of electronic faults. One aspect of the SOTIF approach focuses on identifying scenarios that may exceed the technology and performance limitations of the system, or increase the potential for system misuse by human operators. This paper describes a framework and approach for deriving scenarios that could be used in a SOTIF analysis.

SOTIF OVERVIEW

Figure 1 shows key steps in the SOTIF process as described in PAS 21448. This section describes relevant SOTIF concepts and the reader is referred to PAS 21448 [2] for a more detailed description of the overall SOTIF process.

The SOTIF risk identification and evaluation step determines if credible harm may result from hazardous events. PAS 21448 defines hazardous events as a combination of a potential system hazard and a particular operating situation [2]. Operating situations are defined in ISO 26262 as scenarios¹ that can occur during a vehicle's life [3]. PAS 21448 provides the following example of a hazardous event:

- Hazard: Unintended automatic emergency brake activation at $x \text{ m/s}^2$ for $y \text{ s}$;
- Operation situation: Operating on a highway [2].

After identifying hazardous events, the SOTIF process then focuses on identifying triggering events that may lead to unintended system behavior and ultimately one or more of the identified hazardous events. PAS 21448 defines triggering events, which include foreseeable misuse scenarios, as *driving scenarios with specific conditions that serves as an initiator for a subsequent system reaction* [2]. The analysis of triggering events attempts to identify system weaknesses as well as the related scenarios that could lead to an identified hazardous event [2].

Triggering events can be divided into two classifications.

- The first category contains events that exceed the performance limitations of the system and components. This paper defines triggering events in this category as SOTIF Type I events. This category includes both sensor limitations as well as limitations in algorithms, such as machine learning and neural net algorithms. For example, a highly automated chauffeur system may be operating within its intended operating domain (e.g., highway, good weather) but then encounters a roadway configuration with glare conditions. The resulting lighting conditions may exceed the performance limitations of a front-facing camera.
- The second category contains human factor limitations, particularly in relation to the driver-vehicle interface. This paper defines triggering events in this category as SOTIF Type II events. This area broadly covers several human factors issues, such as the driver failing to keep their hands on the steering wheel; the driver's understanding of the system capabilities and limitations, and the driver's responsibilities; and the driver's ability to understand and respond to warnings and alerts. Under SOTIF, human factor limitations do not extend to intentional abuse of the system, such as intentionally ignoring driver takeover requests or purposely using products intended to override the system limitations.

The scenarios in which triggering events occur are defined in PAS 21448 as a sequence of scenes (i.e., snapshots of the environment) beginning with an initial scene and evolving through a series of events and actions (e.g., triggering events and system responses) [2]. A scene has several characteristics, including dynamic elements, scenery, and self-representations of actors and observers.

According to PAS 21448, scenarios may be classified as known-safe or known-unsafe depending on whether the mitigation strategies sufficiently reduce the SOTIF risk [2]. A third category, unknown-unsafe, represents those scenarios that are not known at the time of system design and are identified through long-term vehicle tests,



Figure 1. Key steps in the SOTIF process [2].

¹ Note that ISO 26262 does not define the term “scenario” as rigorously as PAS 21448.

simulations, random input testing, and other measures.² The approach in this study attempts to improve the initial identification of known-unsafe scenarios through use of a more comprehensive analysis.

APPROACH

Techniques for developing scenarios for SOTIF continues to be a challenge. Some guidance is provided in Annex F of PAS 21448. The approach described in this paper further develops an existing taxonomy to produce a hierarchical framework of variables that could be used to derive scenarios for SOTIF systematically. The intent is to enable a more comprehensive analysis and development of countermeasures by increasing the number of known-unsafe scenarios identified at the outset of the system design. Some elements of a scenario are not covered by the framework, such as system capabilities or programmed system goals and values [2]. The framework is intended to help identify the aspects of a scenario external to the vehicle.

Thorne et al. developed a top-level taxonomy for the operational design domain. The taxonomy identifies 6 top-level categories and 22 immediate subcategories, as shown in Table 1 [4].

Table 1.
Thorne et al. ODD Taxonomy Categories

Top-Level Category	Immediate Subcategory
Physical Infrastructure	Roadway Types
	Roadway Surface
	Roadway Edges
	Roadway Geometry
Operational Constraints	Speed Limit
	Traffic Conditions
Objects	Signage
	Roadway Users
	Non-Roadway User/Obstacles/Objects
Connectivity	Vehicles
	Traffic Density Information
	Remote Fleet Management System
	Infrastructure Sensors and Communications
Environmental Conditions	Weather
	Weather-Induced Roadway Conditions
	Particulate Matter
	Illumination
Zones	Geofencing
	Traffic Management Zones
	School/Construction Zones
	Regions/States
	Interference Zones

This study used the Thorne et al. taxonomy to categorize scenario factors presented in Annex F of PAS 21448 and relevant parameters from the Fatality Analysis Reporting System (FARS).³ The FARS database provides coded variables based on decades of analyzing historical causes of fatal crashes. While FARS does not differentiate between human drivers and driving automation systems, the FARS variables still provide general insight into known challenging roadway conditions and behaviors that driving automation systems may need to navigate.

This study further expanded the Thorne et al. taxonomy as a list of 200 variables categorized into 41 detailed

² SOTIF is an iterative process and unknown-unsafe scenarios, once identified, become known-unsafe scenarios that can be mitigated through modifications of the system design.

³ The FARS database contains information on all crashes on public roadways in the United States resulting in at least one fatality within 30 days of the crash [4].

subcategories, a feature of the SOTIF framework. For some variables and situations, analysts may need to consider the appropriate “negative case” when applying the framework. For example, one variable is “pedestrians, pedal-cyclists, other non-motorist permitted in road.” The corresponding “negative case” is that non-motorists are prohibited from using the roadway. Negative cases are not explicitly included in the framework.

Table 2 provides an example of the expanded framework using roadway type variables from FARS. Attachment A provides the full framework. The scenario variables in Attachment A also include some variables from the Thorne et al. study that were not included in the FARS database [4] and PAS 21448 Annex F [2].

Table 2.
Example Expanded Taxonomy based on FARS and PAS 21448 Parameters

Top-Level Category	Immediate Subcategory	Detailed Subcategory	Scenario Variable
Physical Infrastructure	Roadway Type	Functional Class	Interstate
			Principal Arterial (Other Freeways/Expressways)
			Principal Arterial – Other
			Minor Arterial
			Major Collector
			Minor Collector
			Local
			Other
		Trafficway	Two-way, Divided, Unprotected
			Two-way, Divided, Positive Median Barrier
			Two-way, Not Divided
			Two-way, Not Divided, Continuous Left Turn Lane
			One-way Trafficway
			Non-trafficway or Driveway Access
...

In order to organize the variables from FARS and PAS 21448 further and into a structure amenable to scenario construction, this study categorized each variable as either permanent-regional, permanent-local, a compounding event or condition, or a potential threat.

- Permanent-Regional** – These variables are characteristics of the ODD and form the backdrop of scenarios. Permanent-regional variables do not change over time or over significant spatial portions of the trip. Examples of permanent-regional variables include roadway functional class, lane type, and permitted types of non-vehicle uses. Permanent-regional variables may be most amenable to geocoding because of their persistent and pervasive nature. This study identified 31 scenario variables in the permanent-regional category.
- Permanent-Local** – These variables persist over time, but are localized spatially. From a mobile frame of reference (e.g., a vehicle), permanent-local variables may only be encountered for brief portions of a trip.⁴ A vehicle may encounter multiple permanent-local variables over the course of a trip. Each combination of permanent-local variables may represent different variations of the backdrop defined by permanent-regional variables. Examples of permanent-local variables include curves, hills, bridges, and intersections. Since permanent-local variables are temporally persistent, they could be geocoded—for instance, to inform vehicles of approaching intersections, tunnels, or other similar features. This study identified 44 scenario variables in the permanent-local category.
- Compounding Event or Condition** – These variables are temporary events and conditions that may occur within the scenery defined by permanent-regional and permanent-local variables. For a fixed point in space,

⁴ From a fixed frame of reference (e.g., vehicle-to-infrastructure sensors), permanent-local variables may not be appreciably distinct from permanent-regional variables.

compounding events or conditions are those aspects of the initial scene that can change. While a compounding event or condition may persist through an entire trip (e.g., rain), it is also possible for the same compounding event or condition to persist for only a portion of a trip (e.g., a short rain shower) or to change between trips (e.g., the weather may be clear one day and rainy the next). This study further defines compounding events or conditions as variables that are aspects of normal driving. This study identified 75 compounding event or condition variables.

- **Threats** – These variables are temporary events or conditions that relate to specific roadway threats to which the system may need to respond. Unlike compounding events/conditions, threats represent unexpected behaviors or deviations from normal driving situations—for example, other vehicles disobeying signs or traffic controls or pedestrians darting out into the roadway. Threats may be static (e.g., a stalled or disabled vehicle) or dynamic (e.g., an aggressive driver). This study identified 50 threat variables.

Together, the persistent regional, persistent local, compounding events or conditions, and threats define key aspects of the initial scene. Figure 2 shows the relationship of categories assigned to the FARS and PAS 21448 variables incorporated into the taxonomy.

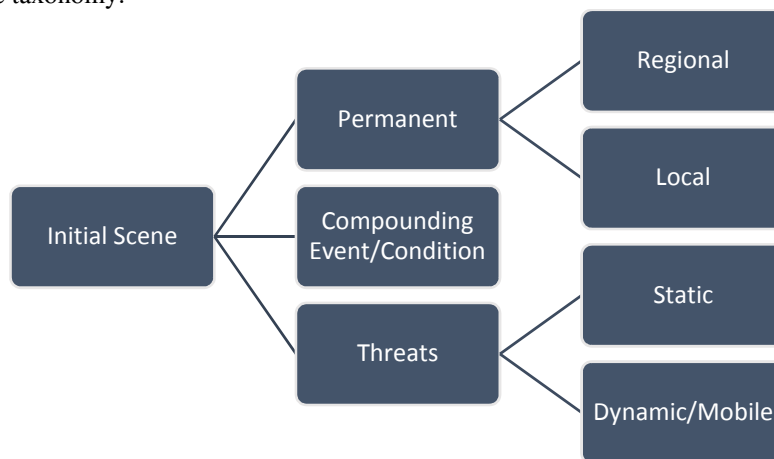


Figure 2. Categorization schema for variables in the taxonomy.

PAS 21448 does not differentiate between temporary and permanent elements of the scene. For instance, PAS 21448 includes “environment conditions” as part of the scenery element [2]. However, the framework presented in this study categorizes environmental conditions (e.g., weather, lighting) under compounding events or conditions that are more akin to other dynamic elements, such as traffic, objects, and pedestrians. Separating out the permanent variables can help identify elements of the scenario that a system could predict with greater confidence. This could be particularly important for systems that rely on transitioning control back to the driver. These variables may be more amenable to geocoding or mapping in order to transfer control to the driver with sufficient time for the driver to regain situational awareness.

This study derived triggering events through analysis of the physical limitations of sensors and probabilistic nature of algorithms (Type I SOTIF events). Analysis techniques such as Systems Theoretic Process Analysis (STPA) were used to derive potential driver misuse scenarios (Type II SOTIF events). For each triggering event, initial scenes were constructed that linked the triggering event to a potential hazardous event to create a SOTIF scenario.

EXAMPLE SCENARIO DERIVATION

This study uses hazardous events and triggering events to constrain the development of scenarios. Note that other approaches to develop scenarios exist and this paper presents only one possible way through which scenarios could be derived. To illustrate this process used in this study, this paper presents examples related to the lane centering maneuver of highly automated chauffeur system. This maneuver attempts to keep the vehicle centered in the travel lane. A prior study by Brewer, et al., identified hazards for a generic lane centering system [5]. A relevant hazard

identified in that prior study is “lane/roadway departure while the system is engaged.”⁵

This study begins developing scenarios by identifying hazardous events. This corresponds to the second step in the SOTIF process shown in Figure 1. The study applied the permanent-regional variables to develop the operating situation for the hazardous event. One example hazardous event derived through this process is:

- Hazard: Lane/roadway departure while the highly automated chauffeur system is engaged
- Operating situation: Operating in a shoulder lane on a two-way divided interstate or freeway/expressway (i.e., restricted access)
- Potential crash type: Sideswipe (same direction of travel)

Permanent-regional variables are the most consistent with the examples of operating scenarios provided in PAS 21448. Permanent-regional variables define the general context of a trip and may be the only variables that persist throughout the segment of the trip in which the system is engaged. Worst-case assumptions can be made about other conditions when assessing the hazardous event at this level.

In developing operating situations, some variable categories may not be relevant to the particular situation. For instance, in the example above, the shoulder type (paved/gravel versus dirt) does not matter. The omission of a variable means that all relevant cases considered are included as subsets of the stated operating situation.

Triggering events were developed independent of the hazardous events, based on system limitations and potential driver misuse. This corresponds to the third step in the SOTIF process shown in Figure 1. Note that in this paper only SOTIF Type I triggering events are considered. Example triggering events developed for highly automated chauffeur system include:

- The lane model algorithm⁶ incorrectly establishes the lane lines.
- The road model algorithm⁷ incorrectly establishes the road model in the absence of clear lane markings.
- The camera fails to detect landmarks because of inadequate contrast between the landmarks and the environment.

At this point in the SOTIF process, system designers may consider functional improvements to mitigate triggering events (Step 4 in Figure 1) and establish testing and acceptance criteria (Step 5 in Figure 1). The next step in the SOTIF process relevant to scenario development is to identify known-unsafe scenarios (Step 6 in Figure 1).

The operating situation used for this hazardous event imposes restrictions on the types of variables to consider in constructing the scenario. For example, since the operating situation is specific to interstate or freeway/expressway (i.e., restricted access) roadways, only certain intersection types need to be considered during development of the initial scene—tollbooth/tollgate and entrance/exit ramp.⁸

The triggering events may also impose restrictions on the types of variables to consider in constructing the scenario. For example, to develop scenarios related to the first triggering event listed above, this study only considers variables and combinations of variables that could affect detection of the lane markings. Similarly, to develop scenarios for the third triggering event, this study considered variables that affect the contrast of lane markings and pavement.

This paper provides three examples of scenarios developed within the constraints of the example hazardous event

⁵ Brewer et al. considered two variations of this hazard based on whether a system fault resulted in excessive or insufficient steering [5]. However, SOTIF presumes that the underlying system is free from faults and therefore this study did not identify a need to differentiate between the two variations of the hazard.

⁶ The lane model algorithm is responsible for identifying the lane boundaries and road edge.

⁷ The road model algorithm establishes a lane for the vehicle based on landmarks in the absence of lane markings or a lead vehicle to follow.

⁸ According to the Federal Highway Administration Highway Functional Classification Concepts [8], some freeways/expressways could have a limited number of at-grade intersections. However, this study assumes that freeways/expressways roadways are more akin to interstates and have restricted access; a possible SOTIF mitigation measure may be to restrict use of the system on freeways/expressways with at-grade intersections.

and triggering events, using the variables presented in the framework.

Table 3.
First Example SOTIF Scenario

Operating Situation	Operating in a shoulder lane on a two-way divided interstate or freeway/expressway (i.e., restricted access)	
Triggering Event	The lane model algorithm incorrectly establishes the lane lines, and the vehicle drifts into the adjacent lane.	
Permanent-Local Variables	<i>Physical Infrastructure → Roadway/Lane Edges → Lane Characteristic</i>	Narrow lanes
Compounding Event or Condition	<i>Operational Constraint → Traffic Conditions → Standard Traffic</i>	Traffic backup due to regular congestion
Threat	<i>Objects → Local Traffic Control Missing</i>	Inadequate warning of exits, narrowing lanes, traffic controls, etc.
Scenario	In heavy traffic, certain roads allow travel on the shoulder lane. However, the shoulder lane might narrow without adequate advance warning that would allow the system to merge out of the shoulder lane. If the vehicle enters a narrower shoulder lane, the lane model algorithm may not be able to determine the appropriate lane width. The system could cross over into the adjacent lane.	

Table 4.
Second Example SOTIF Scenario

Operating Situation	Operating in a shoulder lane on a two-way divided interstate or freeway/expressway (i.e., restricted access)	
Triggering Event	The road model algorithm incorrectly establishes the road model and causes the vehicle to drift into the adjacent lane in the absence of clear lane markings.	
Permanent-Local Variables	<i>Physical Infrastructure → Roadway/Lane Edges → Road Edge Type/Quality</i>	Guard rails
Compounding Event or Condition	<i>Environmental Condition → Weather → Precipitation</i>	Snow
Threat	<i>Physical Infrastructure → Roadway/Lane Edges → Lane Marking Type/Quality</i>	No markings or obscured lane markings
Scenario	Snow may cover the lane markings, making it difficult for the lane model algorithm to track the lane boundaries. Heavy snow may also stick to radars, preventing detection of other landmarks to support the road model algorithm, such as guardrails. Without an appropriate road model, the vehicle may drift out of the shoulder and into the adjacent lane.	

Table 5.
Third Example SOTIF Scenario

Operating Situation	Operating in a shoulder lane on a two-way divided interstate or freeway/expressway (i.e., restricted access)	
Triggering Event	The camera fails to detect landmarks because of inadequate contrast between the landmarks and the environment.	
Permanent-Local Variables	<i>Physical Infrastructure → Roadway Geometry → Alignment</i>	Curve Right
Compounding Event or Condition	<i>Environmental Condition → Light Conditions → Ambient Light</i>	Dark (unlighted)
Threat	<i>Physical Infrastructure → Roadway/Lane Edges → Lane Marking Type/Quality</i>	No markings or obscured lane markings
Scenario	The vehicle is operating on the shoulder at night on an unlit road, and encounters a region without lane markings. A roadway curving to the right may reduce illumination of roadside features by the vehicle's headlights, which may result in inadequate contrast between the landmarks and the environment. The vehicle may drift out of the shoulder lane and into an adjacent lane.	

APPLICATION BEYOND SOTIF

The framework presented in this study could extend beyond SOTIF to provide a general classification of challenging scenarios for driving automation systems. In particular, by separating permanent-regional and permanent-local variables depending on the frame of reference, this framework in this study could help characterize scenarios for vehicle to infrastructure (V2I) and improved GPS mapping (e.g., for geofencing).

Use of a common framework for defining scenarios both in the development of driving automation systems as well as supporting infrastructure could provide consistency between analyses (e.g., types of situations where vehicle-based systems may rely more heavily on V2I). For example, SOTIF scenarios developed using the framework could translate into scenarios where V2I may improve vehicle operation.

CONCLUSIONS

This study established a framework to help develop SOTIF scenarios. The framework combines variables derived from three sources (Thorne et al., PAS 21448, and FARS) into a common typology proposed by Thorne et al. This paper also presents a categorization schema for the variables in the framework to facilitate development of SOTIF scenarios. Certain variables were classified as permanent, with permanence depending on the frame-of-reference (i.e., regional or local features). Non-permanent variables were classified as either compounding events/conditions or threats, based on whether the variable could be anticipated as part of normal driving.

The permanent-regional and permanent-local variables tend not to change over long periods, and can be geocoded with reasonable confidence. If the SOTIF mitigation strategy includes restricting the ODD to avoid certain hazardous events related to permanent-regional or permanent-local variables (e.g., branching or merging lanes), it may be possible to begin alerting the driver with sufficient lead-time through use of detailed maps and GPS. This could increase the probability that the driver will safely resume control of the vehicle. Compounding events or conditions and threats are less predictable and therefore less amenable to geocoding. For instance, a compounding event or condition, or threat may emerge suddenly, necessitating a quick transfer of control to the driver.

The variables presented in this expanded framework can be combined to develop scenarios to support the SOTIF analysis. Three such examples are presented in this paper. Considering a more expanded set of variables and scenarios during the analysis at the outset of the SOTIF process could help reduce the amount of on-road testing and simulation required to identify unknown-unsafe scenarios.

It is important to note that the framework in Attachment A is not intended to be a complete set of *all* relevant variables. Rather, it represents an extension of the taxonomy in Thorne et al. as an effort to progress the state-of-the-art in SOTIF scenario development. The framework presented in this paper could be enhanced by adding additional

factors, such as those observed during real world road tests of driving automation systems. A more complete framework would improve the overall comprehensiveness of the SOTIF analysis.

REFERENCES

- [1] H. Martin, K. Tschabuschnig, O. Bridal and D. Watzenig, "Functional Safety of Automated Driving Systems: Does ISO 26262 Meet the Challenges?," in *Automated Driving: Safer and More Efficient Future Driving*, Springer International Publishing, 2017, pp. 387-416.
- [2] International Organization for Standardization, *PAS 21448: Road vehicles—Safety of the intended functionality*, Geneva: [Author], 2019.
- [3] International Organization for Standardization, *ISO 26262: Road Vehicles—Functional Safety*, Geneva: [Author], 2018.
- [4] E. Thorn, S. Kimmel and M. Chaka, "A Framework for Automated Driving System Testable Cases and Scenarios," NHTSA, Washington, D.C., 2018.
- [5] J. Brewer, C. Becker, L. Yount and J. Pollard, "Functional Safety Assessment of a Generic Automated Lane Centering (ALC) System and Related Foundational Vehicle Systems," National Highway Traffic Safety Administration, Washington, D.C., 2018.
- [6] National Center for Statistics and Analysis, "2012 Fatality Analysis Reporting System (FARS) and National Automotive Sampling System (NASS) General Estimates System (GES) Coding and Validation Manual," DOT HS 811 854, U.S. Department of Transportation, National Highway Traffic Safety Administration, November 2013.
- [7] Federal Highway Administration, "Highway Functional Classification Concepts, Criteria and Procedures," [Author], Washington, DC, 2013.

APPENDIX A: SOTIF SCENARIO FRAMEWORK

Table 6.
Permanent-Regional Variables

Top-Level Category	Immediate Subcategory	Detailed Subcategory	Scenario Variable
Physical Infrastructure	Roadway Type	Functional Class	Interstate
			Principal Arterial (Other Freeways/Expressways)
			Principal Arterial – Other
			Minor Arterial
			Major Collector
			Minor Collector
			Local
			Other
		Trafficway	Two-way, Divided, Unprotected
			Two-way, Divided, Positive Median Barrier
			Two-way, Not Divided
			Two-way, Not Divided, Continuous Left Turn Lane
			One-way Trafficway
			Non-trafficway or Driveway Access
	Roadway Surface and Features	Lane Type	Single Lane
			Multi-lane
			Reversible Lane
			Shoulder Lane
			Managed Lane (HOV, etc.)
		Surface Type	Concrete
			Blacktop, Bituminous, or Asphalt
			Brick or Block (Including Cobblestone/Belgian Brick)
			Slag, Gravel, or Stone
			Dirt
	Roadway/Lane Edges	Shoulder Type	Paved/Gravel
			Unpaved
Objects	Roadway Users	Other Non-Vehicle Users Permitted on Roadway	Pedestrian, Pedal-cyclist, Other Non-motorist Permitted in Road (e.g., Restricted versus Unrestricted)
	Non-Roadway Users	Pedestrian Crosswalks/ Intersections	Crosswalks/Intersections Present in Roadway Type (e.g., Restricted versus Unrestricted)
		Other Users on Side of Roadway	Non-motorists Permitted Along Roadway
Zones	Regions/States	Regional Traffic Laws	Special Regional Traffic Laws and Norms
		State Traffic Laws	Special State Traffic Laws and Norms

Table 7.
Permanent-Local Variables

Top-Level Category	Immediate Subcategory	Detailed Subcategory	Scenario Variable
Physical Infrastructure	Roadway Surface and Features	Intersection	Median Crossover Road
			Tollbooth/Tollgate
			Entrance/Exit Ramp
			Four-way Intersection
			T-intersection
			Y-intersection
			Traffic Circle
			Roundabout
			Five-point or More
			L-intersection
		Surface Type	Local Change in Surface (e.g., Concrete Bridge)
			Step Difference/Uneven
		Roadway Condition	Manhole Cover
	Roadway/Lane Edges	Lane Marking Type/Quality	Bott's Dots or Cat's Eye
			Other Non-Traditional Markings
		Lane Type	Narrow Lane
			Wide Lane
			Merging
			Branching
		Road Edge Type/Quality	Median
			Curb
			Concrete Barrier
			Guardrails
			Grating
			Telephone Poles
	Roadway Geometry	Alignment	Straight
			Curve Right
			Curve Left
		Grade	Level
			Grade, Unknown Slope
			Hillcrest
			Sag (Bottom)
			Uphill
			Downhill
			Banked
Operational Constrain	Speed Limit	Speed Limit Signage	Posted Speed Limit
Zones	Traffic Management Zone	Variable Speed Zone	Variable Speed Zone
		Loading/Unloading Zone	Loading/Unloading Zone
	School/Construction Zone	School Zone	Within Designated School Zone
	Interference Zones	Structures	Tunnels
			Bridges (Double-deck, Covered, Viaduct, etc.)
			Tall Buildings (e.g., Urban Canyon)
			Parking Garage
		Natural Conditions	Geologic Formations (e.g., Canyons, Overhang)

Table 8.
Compounding Event or Condition Variables

Top-Level Category	Immediate Subcategory	Detailed Subcategory	Scenario Variable
Physical Infrastructure	Roadway Surface and Features	Roadway Condition	Ruts, Holes, Bumps in Road
			Other Maintenance or Construction-Related Condition
			Shoulder Related (Design or Condition)
			Inadequate Construction or Poor Design of Roadway, Bridge, etc.
	Roadway/Lane Edges	Road Edge Type/Quality	Cones
Operational Constraints	Speed Limit	Operating Speed	Posted Maximum Limit Below Minimum System Operating Speed
			Posted Minimum Limit Above Maximum System Operating Speed
			Relative Speed Above Surrounding Traffic
			Relative Speed Below Surrounding Traffic
			Speed Inappropriate for Conditions (e.g., Surface, Geometry)
		Speed Limit Signage	None (Inferred Speed Limit)
	Traffic Conditions	Standard Traffic	Light or No Traffic
			Backup Due to Prior Non-Recurring Incident
			Backup Due to Prior Crash
			Backup Due to Regular Congestion
		Altered Traffic Flow	Tollbooth/Plaza Related
Objects	Signals and Signage	Local Traffic Control Type	No Control or Uncontrolled
			Flashing Traffic Control Signal
			Traffic Signal with or without Pedestrian Crossing Signal
			Regulatory Sign
			Warning/Information/Temporary Sign
			Railroad Crossing Device/Gate
			Traffic Officer/Flag Person/Hand Signs
	Roadway Users	Standard Vehicles	Standard Vehicles in Roadway
		Non-Standard Vehicles	Special Cargo Body Type (e.g., Garbage, Gravel, Flatbed, Auto Transporter)
			Large Vehicle Configuration (e.g., Bus, Tractor-Trailer, Single Unit Truck, Etc.)
			Towed Vehicle (Fixed or Non-Fixed Linkage)
			Multiple Trailing Units
			Wide-Load Vehicle
		Other Non-Vehicle Users Permitted on Roadway	Pedestrian, Bicyclist, Other Cyclist or Person on Personal Conveyances in Travel Lane
			Pedestrian, Bicyclist, Other Cyclist or Person on Personal Conveyances on Paved Shoulder/Bicycle Lane/Parking Lane
			Pedestrian Jogging/Running in Roadway

Top-Level Category	Immediate Subcategory	Detailed Subcategory	Scenario Variable
Objects (cont.)	Non-Roadway Users	Pedestrians	Pedestrian, Bicyclist, Other Cyclist, or Person on Personal Conveyances in Intersection Area
			Pedestrian, Bicyclist, Other Cyclist, or Person on Personal Conveyances in Crosswalk Area
			Pedestrian, Bicyclist, Other Cyclist, or Person on Personal Conveyances in Median/Crossing Island
			Pedestrian, Bicyclist, Other Cyclist, or Person on Personal Conveyances Waiting to Cross Roadway
		Other Users on Side of Roadway	Pedestrian, Bicyclist, Other Cyclist, or Person on Personal Conveyances on Sidewalk/Shared-Use Path/Driveway Access
			Pedestrian, Bicyclist, Other Cyclist, or Person on Personal Conveyances in Unpaved Right-of-Way
			Pedestrian, Bicyclist, Other Cyclist, or Person on Personal Conveyances in Non-trafficway (Driveway)
			Pedestrian, Bicyclist, Other Cyclist, or Person on Personal Conveyances in Non-trafficway (Parking Lot/Other)
			Pedestrian, Bicyclist, Other Cyclist, or Person on Personal Conveyances Adjacent to Roadway (e.g., Shoulder, Median)
			Pedestrian Jogging/Running Adjacent to Roadway
Environmental Conditions	Weather	Wind	Severe Crosswind
			Wind from Passing Truck
		Precipitation	Clear/Cloudy
			Rain
			Sleet/Hail
			Snow
			Blowing Snow
			Freezing Rain or Drizzle
		Particulate Matter	Fog, Smog, Smoke
			Blowing Sand, Soil, Dirt
	Weather-Induced Roadway Condition	Roadway Obscured	Surface Under Water
			Splash or Spray from Another Vehicle
		Surface Condition (Including Low- μ)	Wet
			Snow
			Ice/Frost
			Sand
			Water (Standing or Moving)
			Mud, Dirt, Gravel
			Slush
			Surface Washed Out (e.g., Cave-in, Road Slippage)
			Loose or Slippery Surface (Mud, Gravel, Sand, Wet Leaves)
	Light Conditions	Ambient Light	Daylight
			Dark (Lighted)
			Dark (Unlighted)
			Dawn
			Dusk
		External Lighting	Reflected Glare, Bright Sunlight, Headlights

Top-Level Category	Immediate Subcategory	Detailed Subcategory	Scenario Variable
Zones	Special Zone	Special Zone	Special Zone
	School/Construction Zone	School Zone	Pedestrian, Bicyclist, Other Cyclist, or Person on Personal Conveyances Going To or From School (K-12)
		Construction Zone	Construction
			Utility Work
			Maintenance
	Interference Zone	Natural Conditions	Dense Foliage

Table 9.
Threat Variables

Top-Level Category	Immediate Subcategory	Detailed Subcategory	Scenario Variable
Physical Infrastructure	Roadway/Lane Edges	Lane Marking Type/Quality	No Markings or Obscured Lane Markings
Operational Constraints	Traffic Conditions	Altered Traffic Flow	Recent Previous Crash Scene Nearby
			Police Pursuit
			Stalled/Disabled Vehicle or Vehicle Fire
Objects	Signals and Signage	Local Traffic Control Missing	Inadequate Warning of Exits, Narrowing Lanes, Traffic Controls, Etc.
			Traffic Controls Not Functioning Properly
	Roadway Users	Standard Vehicles	[Other Vehicle] Aggressive Behavior by Non-Contact Vehicle Owner
			[Other Vehicle] Overloading or Improper Loading of Vehicle with Passengers or Cargo
			[Other Vehicle] Following Improperly
			[Other Vehicle] Travelling on Prohibited Trafficways
			[Other Vehicle] Passing Through or Around Barrier
			[Other Vehicle] Failure to Observe Warnings or Instructions on Vehicles Displaying them
			[Other Vehicle] Failure to Signal Intentions
			[Other Vehicle] Driving Wrong Way or On Wrong Side
			[Other Vehicle] Other Bad Driving
			[Other Vehicle] Disobeying Signs or Traffic Controls
			[Other Vehicle] Other Driving in the Wrong Place (e.g., Bike Lane)
			[Other Vehicle] Other Misbehavior – Moving (e.g., Not Dimming Headlights)
			[Other Vehicle] Other Misbehavior – Fixed (e.g., Open Door into Trafficway)
			Jackknife of Articulated Vehicle
			Nearby Trailer (Swerving, Swaying, or Fishtailing)
			[Vision Obscured by] In-Transport Motor Vehicle (including load)
		Other Non-Vehicle Users Permitted on Roadway	Non-Occupant Struck Vehicle
			Non-Motorist Inattentive, Careless, Distracted
			Non-Motorist Failure to Yield Right-of-Way
Objects (cont.)	Roadway	Other Non-Vehicle	Non-Motorist Failure to Obey Traffic Signs, Signals, or

Top-Level Category	Immediate Subcategory	Detailed Subcategory	Scenario Variable
	Users (cont.)	Users Permitted on Roadway (cont.)	Officer
			Non-Motorist Improper or Erratic Lane Changing
			Non-Motorist Failure to Keep in Proper Lane or Running Off Road
			Non-Motorist Passing with Insufficient Distance or Inadequate Visibility, or Failing to Yield to Overtaking Vehicle
			Non-Motorist Making Improper Entry To or Exit From Trafficway
			Non-Motorist Making Improper Turn or Merge
			Non-Motorist Improper Passing
			Non-Motorist Not Visible (Dark Clothing, No Lighting, etc.) or Failing to Have Lights On When Required
			Non-Motorist Operating without Required Equipment
			Non-Motorist in Roadway Improperly (Standing, Lying, Working, Playing)
			Non-Motorist Wrong-way Riding or Walking
			Non-Motorist Working in Roadway (Incident Response)
			Non-Motorist Entering/Exiting Parked or Stopped Vehicle
			Disabled Vehicle Related (Working On, Pushing, Leaving/Approaching)
	Non-Roadway Users	Stationary Object	Debris or Objects in Road
			[Vision Obscured by] Curve, Hill, or Other Roadway Design Features
			[Vision Obscured by] Building, Billboard, etc.
			[Vision Obscured by] Trees, Crops, Vegetation
			[Vision Obscured by] Not-in-Transport Motor Vehicle (Parked, Working)
		Dynamic Object	Struck by Falling Cargo or Something that was Set in Motion by Vehicle
			Non-Occupant Struck by Cargo/Debris
			Animal in Road
		Pedestrian	Pedestrian, Bicyclist, Other Cyclist, or Person on Personal Conveyances Dart-out
			Pedestrian, Bicyclist, Other Cyclist, or Person on Personal Conveyances Improper Crossing of Roadway or Intersection (Jaywalking)
			Pedestrian, Bicyclist, Other Cyclist, or Person on Personal Conveyances Crossing Expressway

CONTRAST BETWEEN ROAD AND ROADSIDE MATERIALS FOR ROAD EDGE DETECTION IN VEHICLE ROAD DEPARTURE MITIGATION SYSTEMS

Qiang Yi
Stanley Chien
Yaobin Chen

Transportation Active Safety Institute, Indiana University-Purdue University, Indianapolis
USA

Rini Sherony
Collaborative Safety Research Center, Toyota Motor North America
USA

Paper Number 19-0058

ABSTRACT

Vehicle roadway departure crashes results in a large number of fatalities in the U.S. Road departure mitigation (RDM) systems rely on the road edge and road boundary identification. Cameras are widely used in RDMS for identifying road edges. The contrast between road and road boundary objects is one of the key image features used by the camera to detect road edges. This paper analyzes and compares the contrasts between various road surfaces and road edges.

INTRODUCTION

Road departure (RD) crashes are frequently severe and account for a large number of fatalities in the United States. According to the report from Federal Highway Administration (FHWA), an annual average of 19,233 fatalities resulted from roadway departure from 2015 to 2017, which is 52 percent of all the traffic fatalities in the United States [1].

A road departure crash is defined as “a non-intersection crash which occurs after a vehicle crosses a road edge line or a center line, or otherwise leaves the traveled way” [2]. To effectively prevent RD crashes, the Federal Highway Administration (FHWA) has developed several strategic approaches and plans, which focus on three objectives: 1) Keep Vehicles on Roadway, 2) Provide for Safe Recovery, and 3) Reduce Crash Severity [1]. While these countermeasures implemented by FHWA are all infrastructures related, the new generation vehicles equipped with road departure mitigation (RDM) systems have been developed and introduced into the market in recent years. Vehicle RDM systems rely on sensors to detect the road edge or roadside objects [3, 4]. Three key sensors are used to detect the road edges, including camera, radar, and LIDAR. For the low-profile roadside objects, including grass, curbs, and gravel, the cameras are widely used in RDM systems. In general, camera sensors use multiple features for object recognition. The contrast between road and road boundary objects is one of the key image features, which could significantly affect the detection of the road edges [5, 6].

To support the evaluation of the RDM systems and help to improve the performance of RDM systems, a set of roadside surrogate objects have been developed by the Transportation Active Safety Institute (TASI) at Indiana University-Purdue University Indianapolis (IUPUI) [7-9]. The requirements for these objects are that they should have the same characteristics of the real U.S. roadside objects from the viewpoint of automotive sensors. This paper analyzes and compares the contrasts between various road surfaces and the low-profile roadside objects, including green grass, yellow grass, curbs, and gravels.

Google street view is used to gather the samples of the road and roadside objects in the United States. 24,762 randomly sampled road locations with street view images were used in this study. The road surface and road edge types of all these 24, 762 locations were identified. Considering only the images in which the roads do not have

clear road edge marking, 2,295 samples with green grass, 927 samples with yellow grass, 3,965 samples with curbs, and 771 samples with gravel were examined.

The contrast is defined as a function of gray levels of the road surface (new asphalt, old asphalt, concrete, and others) and roadside object (gravel, green grass, yellow grass, curb). A larger absolute contrast number means a higher contrast. Negative contrast number means that the road is brighter than the roadside; positive contrast number means that roadside is brighter than the road. Histograms are used to describe the sample distribution with respect to the contrast for each combination of the road surface and roadside.

THE ROADSIDE OBJECTS DATASET

Google Street View is used to gather the road/roadside object images in the U.S. The whole processing is shown in Fig. 1. 824,957 road locations in the U.S. were randomly sampled (including Hawaii and Alaska). Since these locations have significantly biased distributions such as concentration in small roads in the large rural areas, a stratified sub-sampling was conducted with the balancing consideration of road levels, geographic locations, and population densities. As a result, 44,000 stratified locations were generated. In our research, the high-resolution satellite top-view images and street-view images of these 44,000 road locations were purchased. Since the top-view images cannot provide sufficient resolution to determine roadside objects and analyze the contrast between roads and roadside objects, the street-view images at these locations were searched. However, only 24,762 out of 44,000 locations have street-view images, which are used in this study [8, 9].

Unlike the lane departure warning (LDW) system that uses the road marking to detect the road or lane markings, RDM systems detect the road edges without road markings or with obscure road markings. Thus, only the locations without road marking or with unclear road marking were considered in this study. As a result, a total 7,958 out of 24,762 locations have the low-profile roadside objects and do not have road markings or have unclear road markings. Among them, 2,295 samples have green grass roadside, 927 samples have yellow grass roadside, 3,965 samples have curbs, and 771 samples have gravel roadside. It should be noted that high profile roadside objects such as metal guardrails, concrete dividers, and traffic barrels are not studied in this paper.

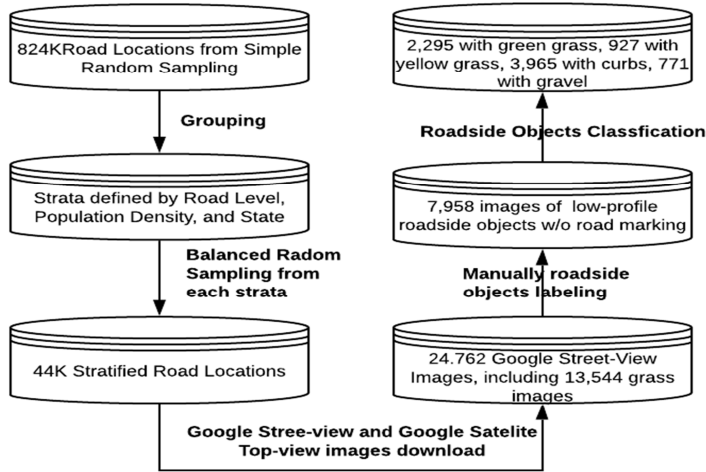


Fig. 1. The process of generating the data set of roadside objects.

THE DEFINITION OF CONTRAST

Contrast study is conducted in grayscale space. It is defined as a function of gray levels of the road surface (e.g., new asphalt, old asphalt, concrete, and others) and roadside object (e.g., gravel, green grass, yellow grass, curb). The calculation is shown in equation (1).

$$Contrast = \begin{cases} \frac{grayValue_{object}}{grayValue_{road}} - 1, & \text{if } \frac{grayValue_{object}}{grayValue_{road}} \geq 1 \\ -\frac{grayValue_{road}}{grayValue_{object}} + 1, & \text{if } \frac{grayValue_{object}}{grayValue_{road}} < 1 \end{cases} \quad (1)$$

This definition gives a continuous real number value. A larger absolute contrast number means higher contrast. If the contrast value is 0, it means that the brightness of the road boundary and road are the same (no contrast). If the contrast value is greater than 0, the roadside is brighter than the road. If the contrast value is less than 0, the road is brighter than the roadside.

To determine the contrast between the road and road boundary objects on an image, the representative samples on the road and roadside need to be gathered. A graphical user interface (GUI) was developed (shown in Fig. 2) to support manual marking on the road edges and to pick the representative sampling points on the image.

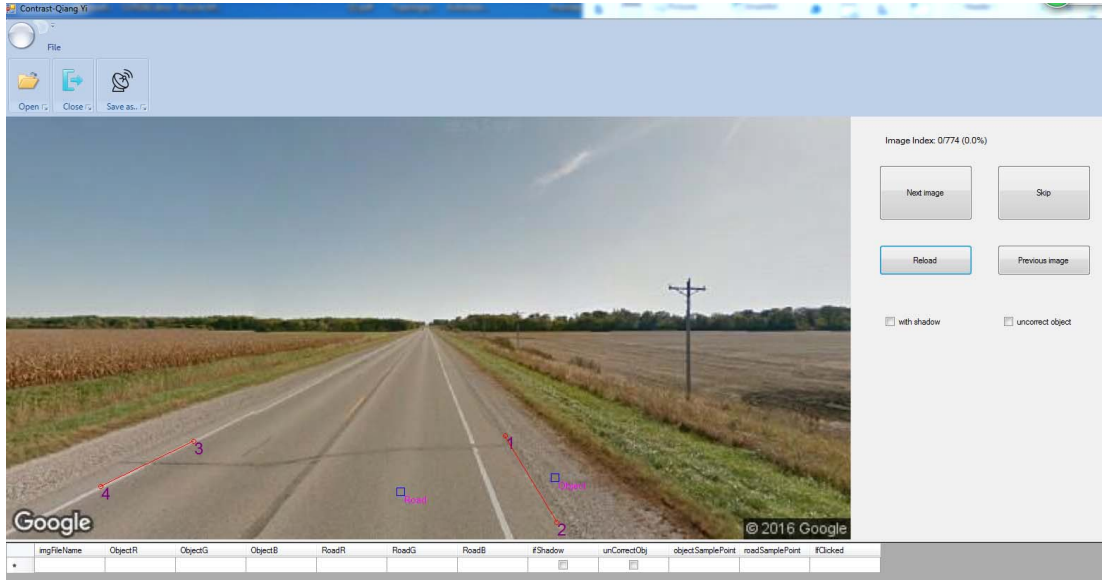


Fig. 2. The GUI for road edges marking and sample point selection.

THE RESULTS AND DISCUSSION

The contrast between roads and the road boundary with green grass

2,295 sample images of roadside green grass, which cover different road levels in the U.S. were used to obtain the contrast between the green grass and the road. Among these 2,295 sample images, 1,969 images have asphalt road, 98 images have a concrete road, and 228 have other types of road. Other types of the road include dirt, gravel, snow-covered road and wet road. It should be noted that the green grass and yellow grass was separately discussed because of their obvious visual differences. The definition of green and yellow grass could be found in [9].

Fig. 3 shows the overall distribution of contrasts of all road samples with the green grass road boundary. The horizontal axis is the contrast value; the vertical axis is the sample count. As shown in this Fig. 3, the contrast varies significantly, spreading from -5.13 to 1.23. The maximum distribution falls in the range of -0.3 to -0.2. Fig. 4 to Fig. 6 show the contrast distributions of the green grass boundary with different road types including asphalt, concrete, and others. The contrast distribution with asphalt road is similar to that of the overall roads. It spreads from -5.13 to 1.23. The range with -0.3 to -0.2 has the highest distribution. Different from that of the asphalt roads, contrasts between concrete roads and green grass roadside concentrate on the range of -0.65 to -0.25. They cover 62.2% of the concrete roads. The distribution of contrasts between green grass roadside with other types of roads including dirt,

gravel, snow-covered road and wet road shows a similar tendency with the overall distribution, but it is more concentrated. About 62.7% of the other types of road fall in the range of -0.6 to -0.2.

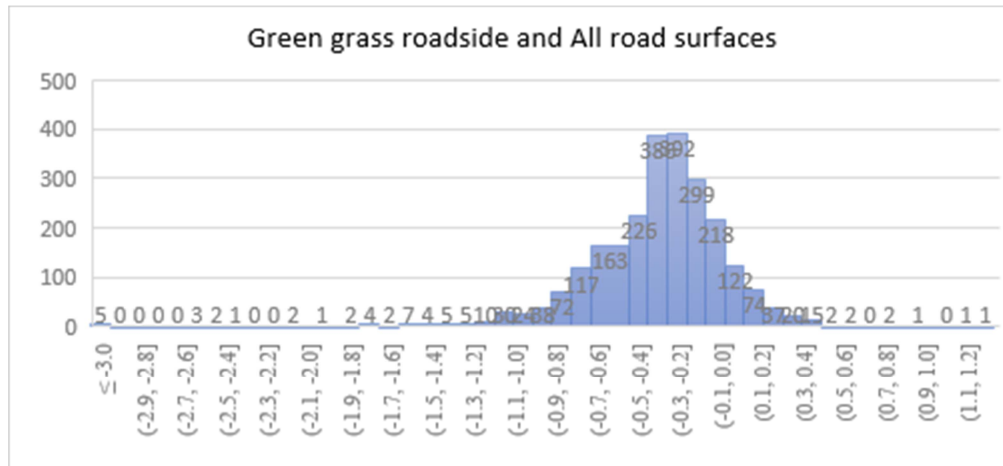


Fig. 3. The distribution of contrasts between all roads and green grass road boundaries.

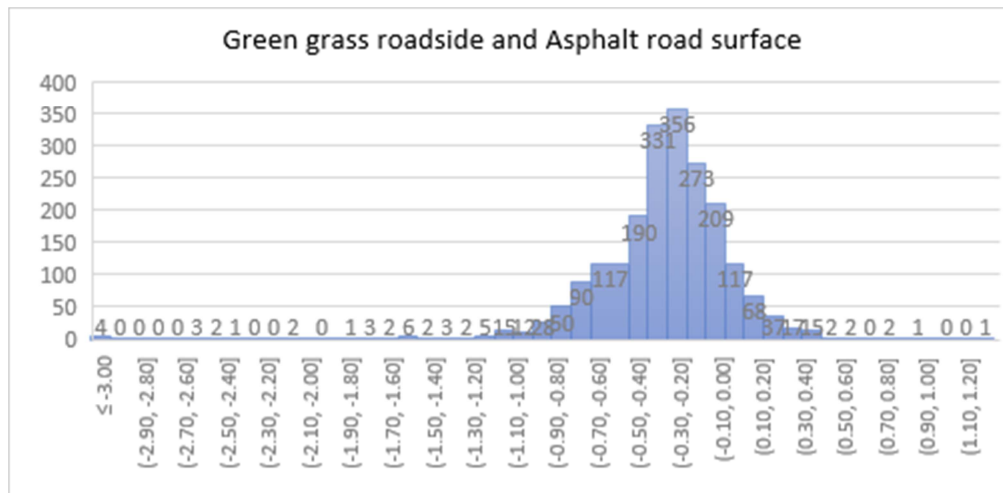


Fig. 4. The distribution of contrast between asphalt roads and green grass road boundaries.

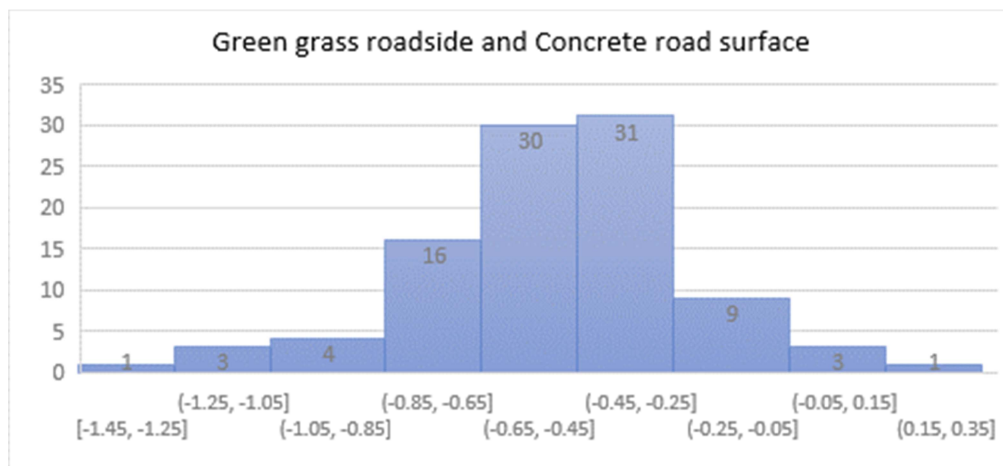


Fig. 5. The distribution of contrasts between concrete roads and green grass road boundaries.

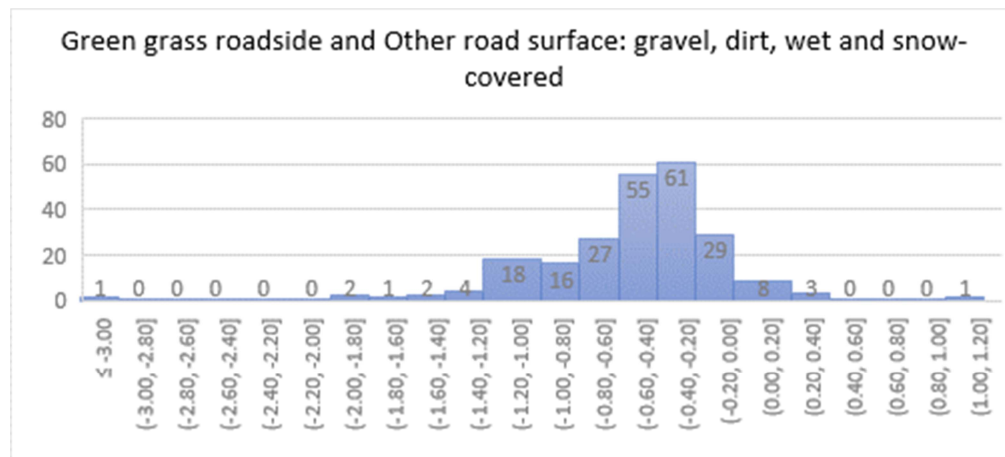


Fig. 6. The distribution of contrasts between other road types (including dirt, gravel and wet) and green grass road boundaries.

The contrast between all roads and the road boundary with yellow grass

927 sample images with yellow grass roadside were used to obtain their contrast. Among them, 827 images are with asphalt road, 14 images are with concrete road, and 86 with other types of road, including dirt, gravel, and wet road.

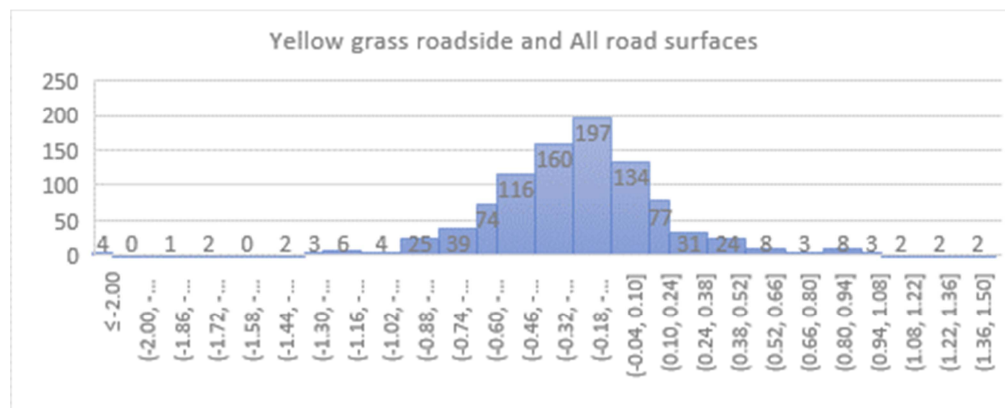


Fig. 7. The distribution of contrasts between all roads and yellow grass road boundaries.

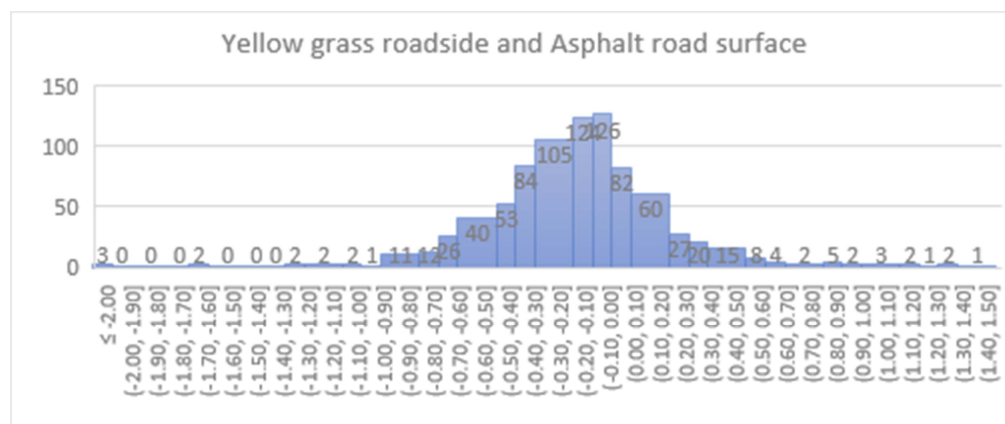


Fig. 8. The distribution of contrasts between asphalt roads and yellow grass road boundaries.



Fig. 9. The distribution of contrasts between concrete roads and yellow grass road boundaries.

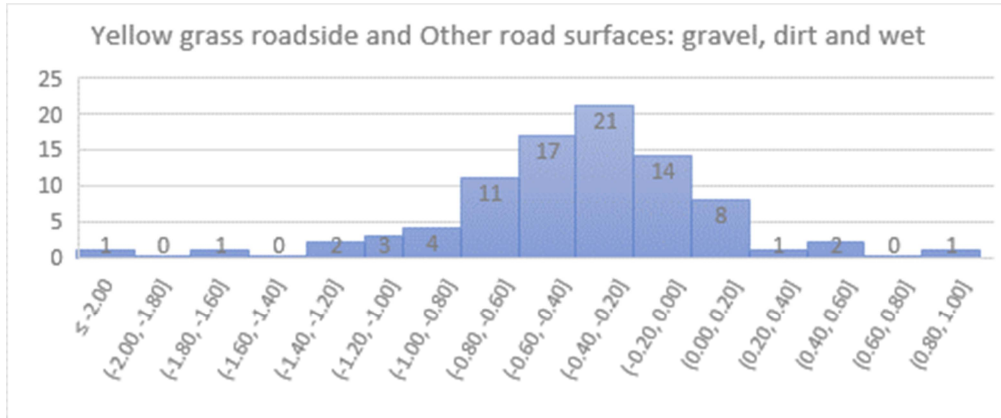


Fig. 10. The distribution of contrasts between other road types and yellow grass road boundaries.

The overall contrast distribution is shown in Fig. 7. It is similar to green grass, but the range is much narrower and more concentrated. The range varies from -2.27 to 1.47. The maximum distribution falls in the range of -0.18 to -0.04. Fig. 8 to Fig. 10 show the contrast distribution of different road types with yellow grass roadside. For the asphalt, the range -0.3 to 0 covers 42.9% of the asphalt roads. For the concrete road, only 14 samples are found. The contrast varies from -0.85 to -0.04. For other types of road, the highest frequency is in the range of -0.4 to -0.2.

The contrast between roads and curbs

Curb is the most common road edge in the U.S. without considering road edge marking. 3,965 images were used to obtain the contrast between the roads and curb. Among them, 3,673 images have asphalt roads, 248 images have concrete roads, and 44 images have other types of roads (including dirt, gravel, and wet road). Fig. 11 shows the distribution of contrast in all 3,965 samples. The range spreads from -3.81 to 2.66. The highest portion is in the range of 0.1 to 0.2. The asphalt road has the same distribution with the maximum distribution in the range of 0.1 to 0.2 (shown in Fig. 12). The contrast between curbs and concrete roads is low, and the highest portion goes to 0 to 0.1 (shown in Fig. 13). For other road types, the range of -0.1 to 0.3 covers 52.3 % of samples (see Fig. 14).

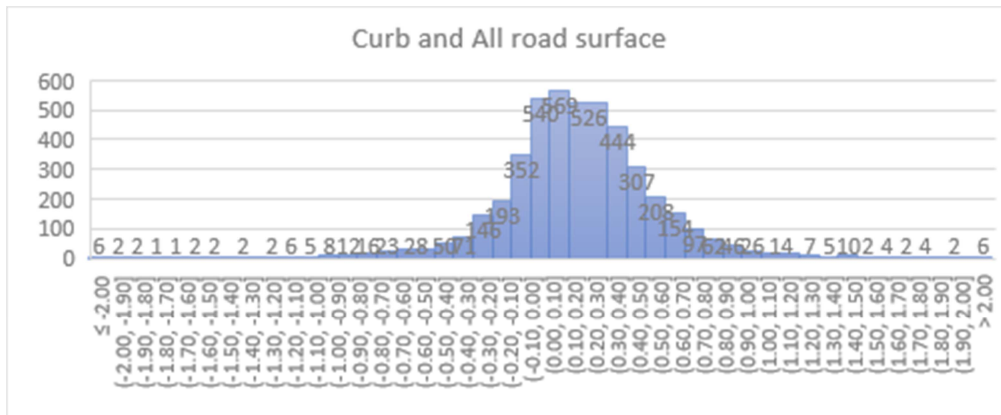


Fig. 11. The distribution of the contrast between all roads and curb road boundaries.

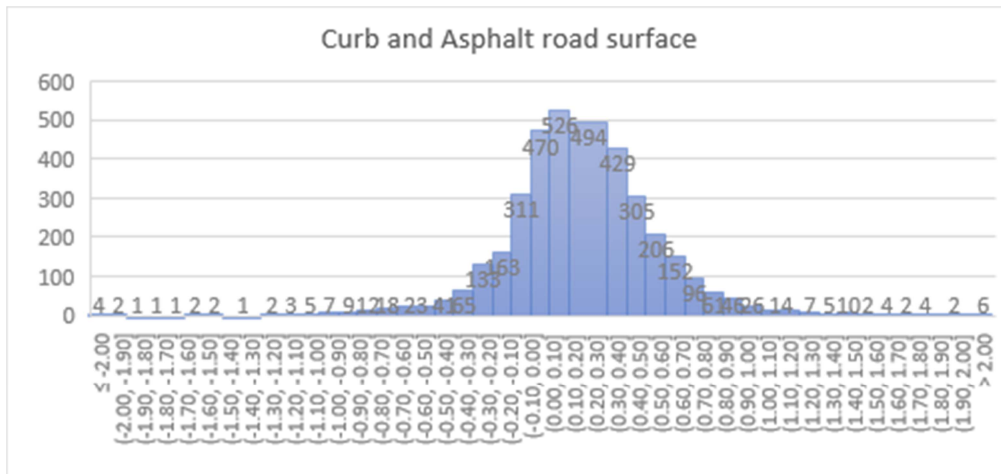


Fig. 12. The distribution of contrasts between asphalt roads and curb road boundaries.

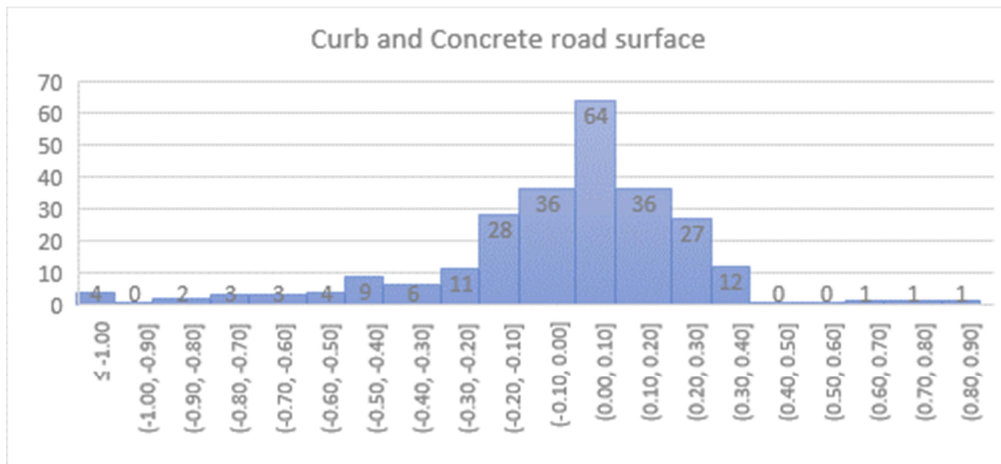


Fig. 13. The distribution of contrasts between concrete roads and curb road boundaries.

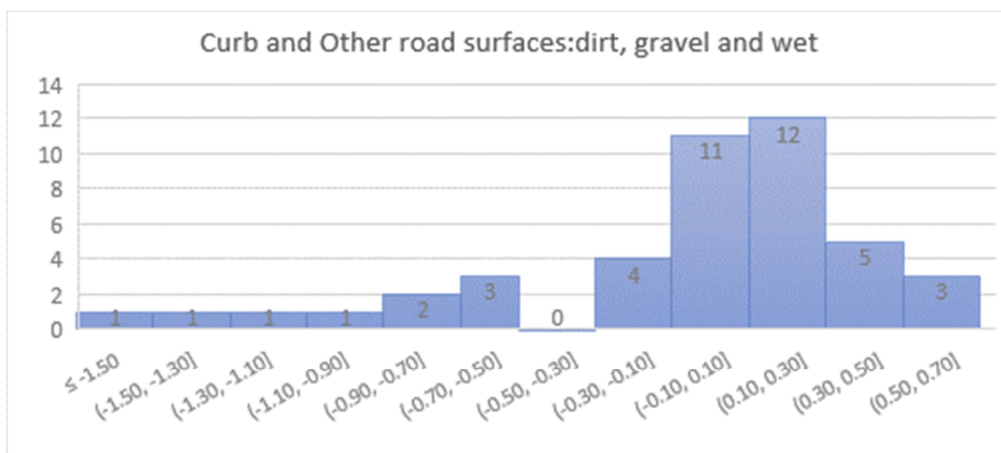


Fig. 14. The distribution of contrasts between other road types and curb road boundaries.

The contrast between the road and the gravel road boundary

771 sampled images with gravel road boundary were used to obtain the contrast. Among them, 698 images have asphalt road, 60 images have concrete roads, and 13 have other types of roads (including dirt, gravel, and wet road). Fig. 15 shows the overall contrast distribution. Comparing with other road boundaries, the contrast between all roads and gravel roadside is relatively low. The range varies from -1.73 to 2.02. The maximum distribution is in the range of -0.1 to 0. Fig. 16 to Fig. 18 show the contrast distribution of curb with asphalt, concrete, and other road types, respectively. The highest distributions are 0.1-0.2, -0.13-0.07 and 0.27-0.23, respectively.

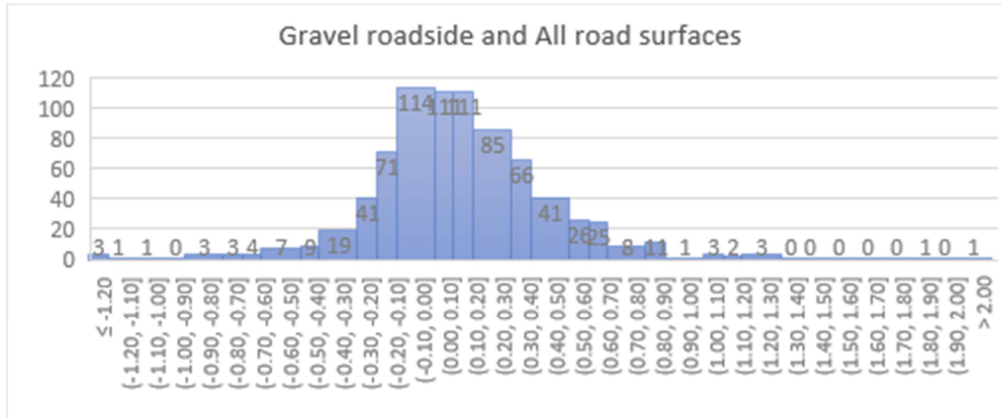


Fig. 15. The overall distribution of contrasts between roads and gravel road boundaries.

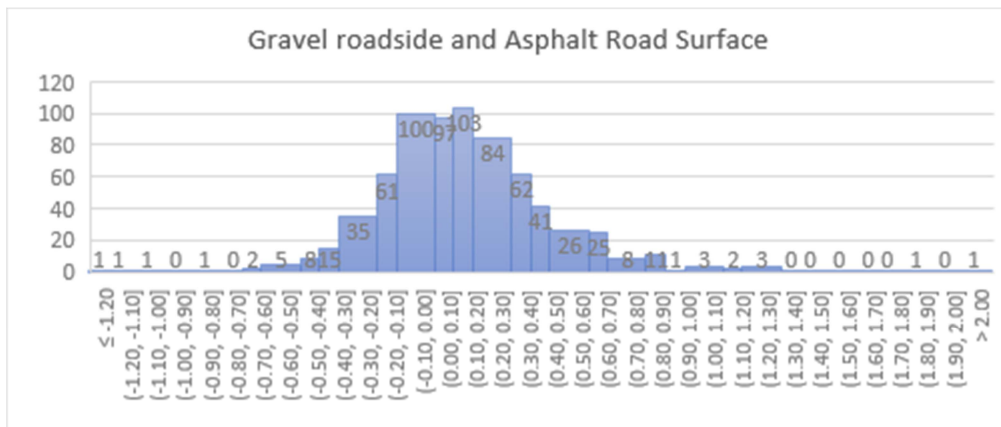


Fig. 16. The distribution of contrasts between asphalt roads and gravel road boundaries.

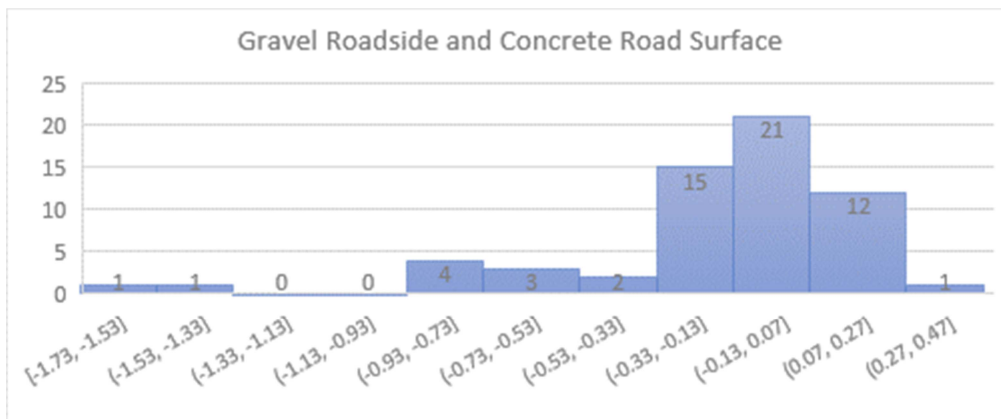


Fig. 17. The distribution of contrasts between concrete roads and gravel road boundaries.

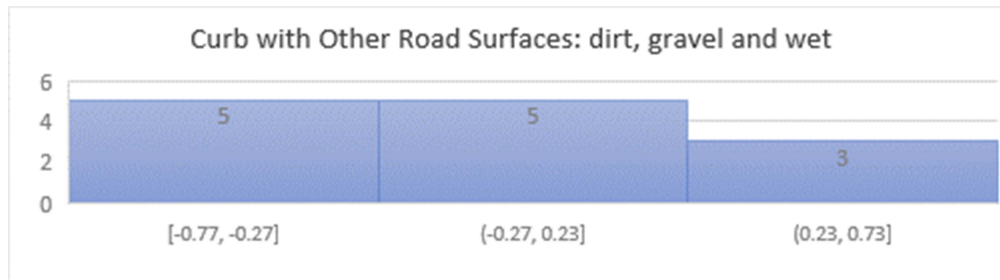


Fig. 18. The distribution of contrasts between other road types and gravel road boundaries.

CONCLUSIONS

This paper provides a contrast definition for analyzing the contrast between various road surfaces and the commonly seen low-profile roadside objects. Contrast values were surveyed based on randomly sampled 7,958 Google street-view images. The range and distribution pattern of contrast between the combination of the road surfaces and roadside were obtained and discussed.

The contrast of asphalt roads and green grass roadsides spreads from -5.13 to 1.23, but most frequently seen contrast is between -0.3 and -0.2. The contrast of concrete roads and green grass roadside spread from -0.45 to 0.15 with 62.2% concentrates between -0.65 and -0.25. The contrast between the concrete road and the curb is from -1 to 0.4 with the majority between -0.2 and 0.2, that means small or no contrast. The most frequently seen contrast of old asphalt road and yellow grass is in the range of -0.1 to 0. Table 1 is a summary of contrast range between different road surfaces and roadside object types, which covers the highest percentage of the samples in descending order. A positive value means that the roadside is brighter than the road. A negative value means that the road is brighter than the roadside.

Table 1.
Summary of the contrasts between road surfaces and roadsides

	Asphalt road	Concrete road	Other roads	Note
Green grass	$[-0.3, -0.2]$	$[-0.45, -0.25]$	$[-0.4, -0.2]$	Road is brighter
Yellow grass	$[-0.1, 0]$	$[-0.55, -0.25]$	$[-0.4, -0.2]$	Road is brighter
Gravel	$[0.1, 0.2]$	$[-0.13, 0.07]$	$[-0.77, 0.27]$	Similar to road
Curb	$[0.1, 0.2]$	$[0, 0.1]$	$[0.1, 0.3]$	Curb is brighter

ACKNOWLEDGMENT

This research was sponsored by the Toyota Collaborative Safety Research Center.

REFERENCES

- [1] "Roadway Departure Safety." https://safety.fhwa.dot.gov/roadway_dept/. March 2019.
- [2] "Roadway Departure Countermeasures," https://safety.fhwa.dot.gov/roadway_dept/rdctrm.cfm. March 2019.
- [3] Katzourakis, D.I., de Winter, J.C., Alirezaei, M., Corno, M. and Happee, R., "Road-departure prevention in an emergency obstacle avoidance situation." *IEEE transactions on systems, man, and cybernetics: systems* 44, no. 5 (2014): 621-629.
- [4] Gray, A., Ali, M., Gao, Y., Hedrick, J. and Borrelli, F., "Semi-autonomous vehicle control for road departure and obstacle avoidance." *IFAC control of transportation systems* (2012): 1-6.
- [5] Charbonnier, P., Nicolle, P., Guillard, Y. and Charmer, J., 1998, September. "Road boundaries detection using color saturation." *9th European Signal Processing Conference (EUSIPCO)*, pp. 1-4. IEEE, 1998.
- [6] Kong, H., Audibert, J.Y. and Ponce, J., 2010. "General road detection from a single image." *IEEE Transactions on Image Processing* 19, no. 8 (2010): 2211-2220.
- [7] Qiang Yi, Dan Shen, Jun Lin, Stanley Chien, and Rini Sherony, "The Color Specification of Surrogate Roadside Objects for the Performance Evaluation of Roadway Departure Mitigation Systems," *SAE Technical Paper 2018-01-0506*, 2018, doi: 10.4271/2018-01-0506.

- [8] Dan Shen, Jun Lin, Qiang Yi, Renran Tian, Stanley Chien, Rini Sherony, "Roadside Boundaries and Objects for the Development of Vehicle Road Keeping Assistance System," SAE Technical Paper 2018-01-0508, 2018, doi: 10.4271/2018-01-0508.
- [9] Qiang Yi, Dan Shen, Jun Lin, Stanley Chien, Lingxi Li, Yaobin Chen, Rini Sherony, "Color and Height Characteristic of Surrogate Grass for the Evaluation of Vehicle Road Departure Mitigation System," 2019 SAE World Congress, Detroit Michigan, April 2019, SAE Technical Paper 2019-01-1026 .

DETERMINE CHARACTERISTICS REQUIREMENT FOR THE SURROGATE ROAD EDGE OBJECTS FOR ROAD DEPARTURE MITIGATION TESTING

Stanley Chien

Qiang Yi

Jun Lin

Abir Saha

Lin Li

Yaobin Chen

Indiana University-Purdue University Indianapolis

USA

Chi-Chih Chen

Ohio State University

USA

Rini Sherony

Collaborative Safety Research Center, Toyota Motor North America

USA

Paper Number 19-0059

ABSTRACT

Road departure mitigation system (RDMS), a vehicle active safety feature, uses road edge objects to determine potential road departure. In the U.S., 45%, 16%, and 15% of car-mile (traffic flow * miles) roads have grass, metal guardrail, and concrete divider as road edge, respectively. It is difficult to test RDMS with real roadside objects. Lightweight and crashable surrogate roadside objects that have representative radar, LIDAR and camera characteristics of real objects have been developed for testing. This [paper describes the identification of automotive radar, LIDAR, and visual characteristics of metal guardrail, concrete divider, and grass.](#) These characteristics will be referenced for designing and fabricating the representative surrogate objects for RDMS testing. Colors and types of the roadside objects were identified from 24,735 randomly sampled locations in the US using Google street view images. The radar and LIDAR parameters were measured using 24GHz/77GHz radar and 350-2500nm IR spectrometer.

Metal guardrail: The peak 24GHz RCS (Radar Cross Section) of W-beam and I-beam of guardrail are 10dB and 13dB. The peak 77GHz RCS for W and I-beam are 15dB and 20dB. When the radar beam direction is not perpendicular to the metal guardrail surface, the reflectivity decreases significantly. As the illumination/measurement angle increases from 0 to 70°, the IR reflectance of metal guardrail decreases from 1.3 to 0.1, and the variation among samples decreases from 1.5 to 0.05. The age of the metal guardrail does not affect the RCS if steel rust is not present.

Concrete divider: Both 24GHz and 77GHz radar reflectivity are -7.3dB. The age of the concrete divider does not affect the radar reflectivity, but the surface smoothness and material affect the reflectivity. As the illumination/measurement angle increases from 0 to 70°, the IR (Infrared) reflectance of concrete divider increases by only 0.1.

Grass: The peak 77GHz RCS is -18dB at 10° depression angle. Different kinds of grass (wild vs. maintained, short vs. long, even vs. uneven) have similar RCS value when measured under the same conditions (same radar type, same polarization, and same pitch angle). Same grass field will produce different RCS during different seasons or after rain where the moisture content of grass produces different reflectivity. As the illumination/measurement angle increases from 0 to 70°, the IR reflectance of grass increases from 0.1 to 1 and the variation among samples increases from 0.2 to 1. The most representative grass road-edge is uneven yellow/green mixed short grass followed by even green and short grass. 18 most occurring grass color patterns were selected.

INTRODUCTION

According to the U.S Department of Transportation Federal Highway Administration, over half of the fatal vehicle crashes were related to road departure [1]. A vehicle road-departure crash is defined as when the vehicle moves from the road to the roadside and consequently leads to a crash [2, 3]. Road departure warning (RDW) and road keeping assistance (RKA) [4-12] are the new technology for reducing road departure crashes [13, 14]. The road departure detection can be based on the recognition of road edge markings. However, many US roads do not have road edge marking or clear road edge marking. Therefore, road edge detection needs to rely on the detection of roadside objects, such as grass, concrete divider, metal guardrail, etc. As RDW and RKA technologies are based on the detection of a roadside object, their performances need to be tested with the roadside objects. The performance testing of the RDW and RKA cannot be on the road with real roadside objects. Testing the RKA on the road with a real concrete divider or real metal guardrail is quite difficult. Testing the RDA on the road with grass road edge is also difficult. The test track may not have a proper grass road edge for RKA tests. To support the performance testing of RDW and RKA, surrogate roadside objects need to be developed so that the test can be performed on the test track repeatedly. Transportation Active Safety Institute (TASI) of Indiana University–Purdue University Indianapolis (IUPUI) studied the development of surrogate roadside objects for RDW and RKA testing with the support of Toyota Collaborate Safety Research Center (CSRC). This paper summarizes the representative shape, color, radar, LIDAR characteristic of the commonly seen roadside objects, such as concrete divider, metal guardrail, and grass. These characteristics can be used as the characteristics requirements for designing and fabricating the object surrogates. The design and fabrication of object surrogates are not in the scope of this paper and will be described in other papers.

MOST COMMON ROADSIDE OBJECTS

In our previous study [15], we sampled 24,762 Google Street view locations all over the United States. Based on location counts, we found that 55% locations have grass edge, 16% locations have concrete curbs, 8.68% locations have a metal guardrail, and 4.17% locations have the concrete divider as the road boundary. If we consider the traffic density on these locations (based on car-miles), we found that 44.6% locations have grass edge, 9.9% locations have concrete curbs, 16.1% locations have metal guardrails, and 15.3% locations have concrete dividers as the road boundary. Since concrete curb is mostly on the city roads with low-speed limits and RDW and RKA are mainly designed for roads with higher speed limits, metal guardrail, concrete divider, and grass road edges are the most common road edges detected by RDW and RKA. Since camera, 24 GHz and 77GHz radar, and automotive 800-1100 nm LIDAR are the most common sensors used for object detection in vehicle active safety, the scope of this paper is to present the representative characteristics of metal guardrail, concrete divider, and grass in the view of the camera, 24 GHz and 77GHz radar, and automotive 800-1100 nm LIDAR.

SPECIFICATIONS OF SURROGATE METAL GUARDRAIL

Physical Shape of the Representative Metal Guardrail

In aforementioned 24,735 randomly sampled road locations in the US, 2150 locations have various types of metal guardrails on the roadside. 81% of these 2,150 metal guardrails has horizontal W-beam with I-beam support (Fig. 1). The representative shape specifications of W-beam and I-Beam in the US can be found in [16]. The representative RGB color of the metal guardrail is (138,139,139) [17]. The physical shape specification of metal guardrail in other countries may be different.






RGB	Range (10% brightness)	
138, 139, 139	168, 168, 168	112, 113, 112
		

Fig. 1. Representative metal guardrail W-beam (left), and color (right).

Radar Characteristics Specifications of Representative Metal Guardrail

Since the metal guardrail surrogate is composed of the W-beam surrogate and the I-beam surrogate, the 24GHz and 77GHz RCS of five W-beams and I-beams were measured. The objects were placed on a rotating table, and their RCS at various angles were measured. The representative RCS of these objects are plotted in Fig. 2 to Fig. 5. Arrows in these figures and orientation of these objects show the viewing angles of the W-beams (blue) or I-beams (gray). The important RCS values that show the characteristics of the objects with respect to the viewing angles are circled. A variation of $\pm 2\text{dB}$ for each circled value is observed with different samples. It was found that the age of the guardrail has little effect on their RCS values (assume the guardrail is not rusted).

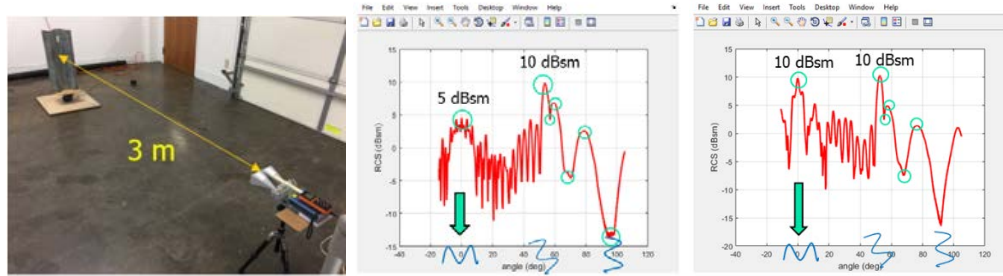


Fig. 2. 24GHz RCS of W-beam. Measurement (left), vertical polarization (middle) horizontal polarization (right).

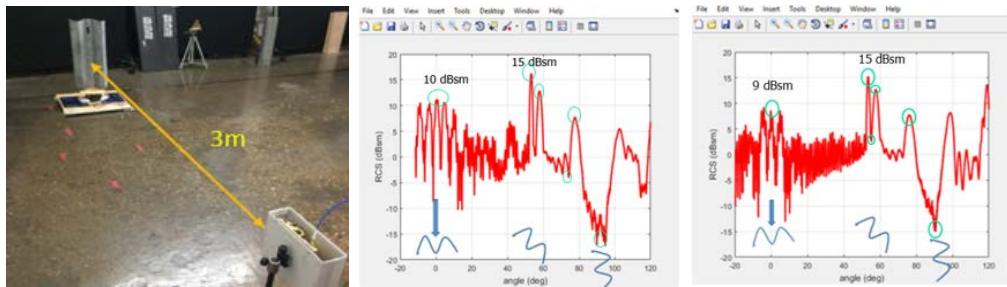


Fig. 3. 77GHz RCS of W-beam. Measurement (left), vertical polarization (middle) horizontal polarization (right).

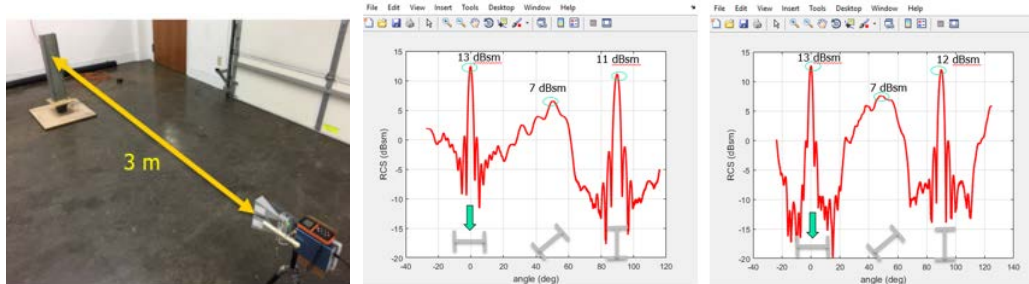


Fig. 4. 24GHz RCS of an I-beam. Measurement (left), vertical polarization (middle), horizontal polarization (right).

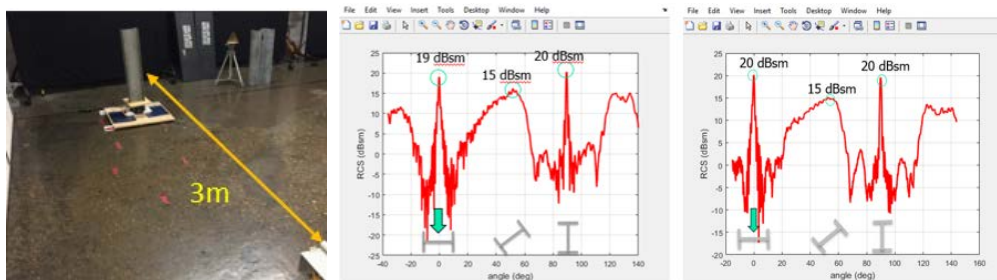


Fig. 5. 77 GHz RCS of an I-beam. Measurement (left), vertical polarization (middle), horizontal polarization (right).

LIDAR Characteristics of Representative Metal Guardrail

There is not a standard laser wavelength for the automotive LIDAR. Common automotive Lidar's wavelengths are in the range of 800-1100nm. We used a spectrometer to measure the diffusive reflectivity of 4 galvanized metal surface samples at various viewing angles. The light source and the measurement probe were put as close as possible to mimic the LIDAR operation. Multiple points on each sample surface were measured. Fig. 6 shows the upper and lower boundaries of the representative IR reflectivity of metal guardrail surface in various laser wavelengths at various measurement angles. 0 degree means that the LIDAR beam is perpendicular to the surface being measured. Since the IR reflectivity variation is small and we do not have a large sample set, the upper bound is the measured maximum reflectivity value plus 0.02, and the lower bound is the measured minimum reflectivity value minus 0.02. It can be seen that the IR reflectivity of the metal guardrail decreases as the viewing angle is getting away from the perpendicular direction to the measured surface. The diffusion reflectivity is only applicable for diffusion surface and should be less than 1 in concept. However, the metal guardrail shows the specular reflection property when measured in low angles (0 to 15 degrees) and shows the diffusion reflection property when measuring in high angles (20 degrees and up).

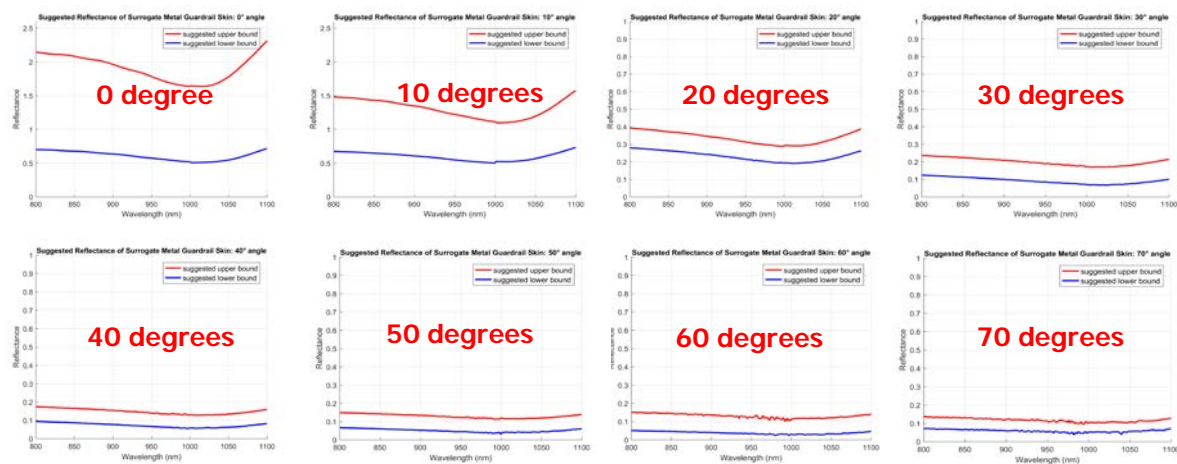


Fig. 6. Suggested IR reflectance range of metal guardrail surface from various viewing angles.

SPECIFICATIONS OF CONCRETE DIVIDER AND CURB SURROGATES

Physical Shape of the Representative Divider and Curb

Concrete curb has many different shapes. In aforementioned 24,735 randomly sampled road locations obtained from Google Street View images, 66% of the 856 concrete dividers observed are in F shape, New Jersey, and single slop shapes. We selected F-shape as the representative shape of the concrete divider. The representative shape specifications of F-shape concrete divider and curb in the US are shown in Fig. 7 [15]. The representative RGB color of concrete divider and curb in the US is (168, 161, 149) [17]. The representative shape and color of the concrete divider in other countries may be different.



Fig. 7. Standard dimensions F-shaped concrete divider (left) curb (right).

Radar Characteristics of Representative Concrete Divider and Curb

Since the concrete divider has a large flat surface, its radar characteristics cannot be described by RCS. Therefore, we use the radar reflectivity to describe the radar property of the concrete divider surface. The proper surface reflectivity property and the correct shape of the surrogate will make it have the correct radar property of a real concrete divider. According to the 24GHz and 77GHz radar reflectivity measurements, forward-looking radar cannot detect concrete divider from a depression angle greater than 15 degrees. So all reflectivity measurement is measured with the radar beam perpendicular to the concrete surface. The measurement results of 7 concrete dividers and curbs suggested that both the representative 24GHz and 77GHz radar reflectivity of common smooth concrete divider surface are -7.3 ± 1 dB under dry condition. The average reflectivity of concrete dividers with smooth surfaces are similar. As the surface is damaged with scratches, the reflectivity varies significantly. The radar reflectivity of the concrete surface increases with the increase in humidity. The color, protective coating, and age of the concrete dividers do not affect their radar reflectivity.

LIDAR Characteristics of Representative Metal Guardrail

A spectrometer that covers a large range of laser wavelength was used to measure the diffusive reflectivity of 7 concrete dividers and curbs of various ages at a range of viewing angles. The light source and the measurement probe were put as close as possible to mimic the LIDAR operation. Multiple points in each sample were measured. Fig. 8 shows the upper and lower boundaries of all measurements at various angles, where 0 degree means that the LIDAR beam is perpendicular to the surface being measured. The upper bound is the measured maximum reflectivity value plus 0.05, and the lower bound is the measured minimum reflectivity value minus 0.05. It can be seen that the IR reflectivity of the concrete surface increases as the viewing angle is getting further away from the perpendicular direction to the concrete surface. The concrete surface is diffusive in all viewing angles.

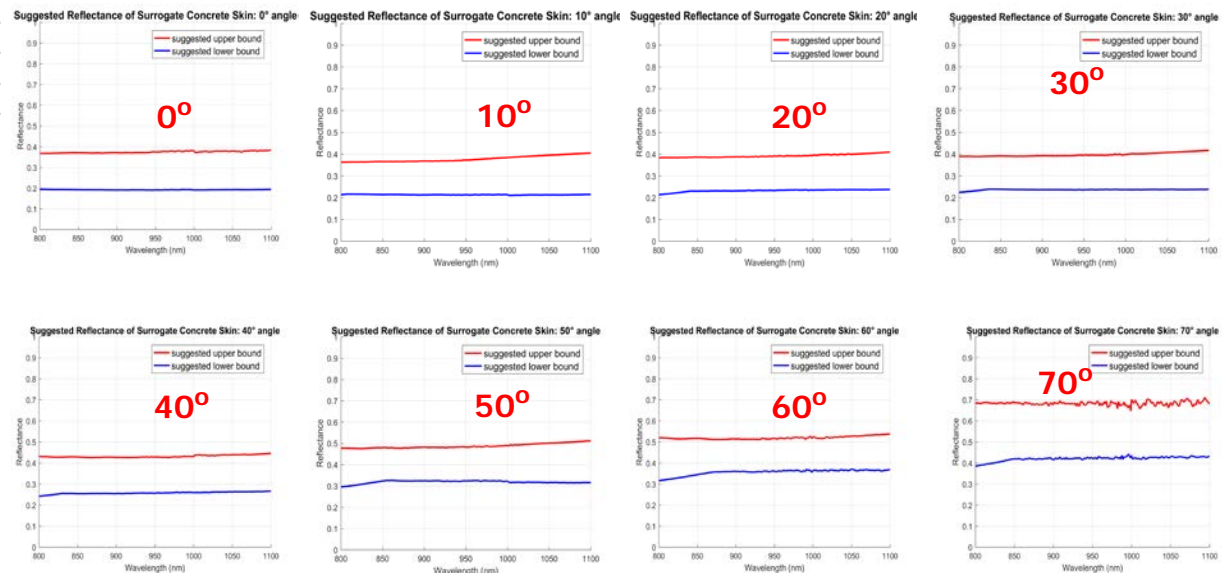


Fig. 8. Representative IR reflectance range of concrete surface from various viewing angles.

SPECIFICATIONS OF GRASS SURROGATES

Height and Color of Representative Grass

In the aforementioned 24,762 Google Street View images, the RGB color of 901 grass images in good weather and not under the shade were studied. The heights of grass in the images were estimated based on over 70 reference road images with known grass height of the grass road edge. The conclusion was that the height of over 80% roadside grass was short (2-4") or medium (5-10"), about 46% of the roadside grass were mixed green and yellow, about 30% grass was green, and rest was brown/yellow. The color of the grass samples was clustered into 6 groups with the representative color as shown in Table 1. Since the grass color patterns have vast variations, we clustered the 901 grass samples and generated 18 color patterns (see

Fig. 9). For each color pattern, the left is an example image, and the right is the actual color pattern. Each color pattern can be a mix of several colors identified in Table 1.

Table 1.
Representative color components of grass.

Color	Yellow			Green		
R,G,B	111, 95, 65	146, 130, 96	170, 162, 135	99, 100, 55	105, 110, 44	139, 141, 87

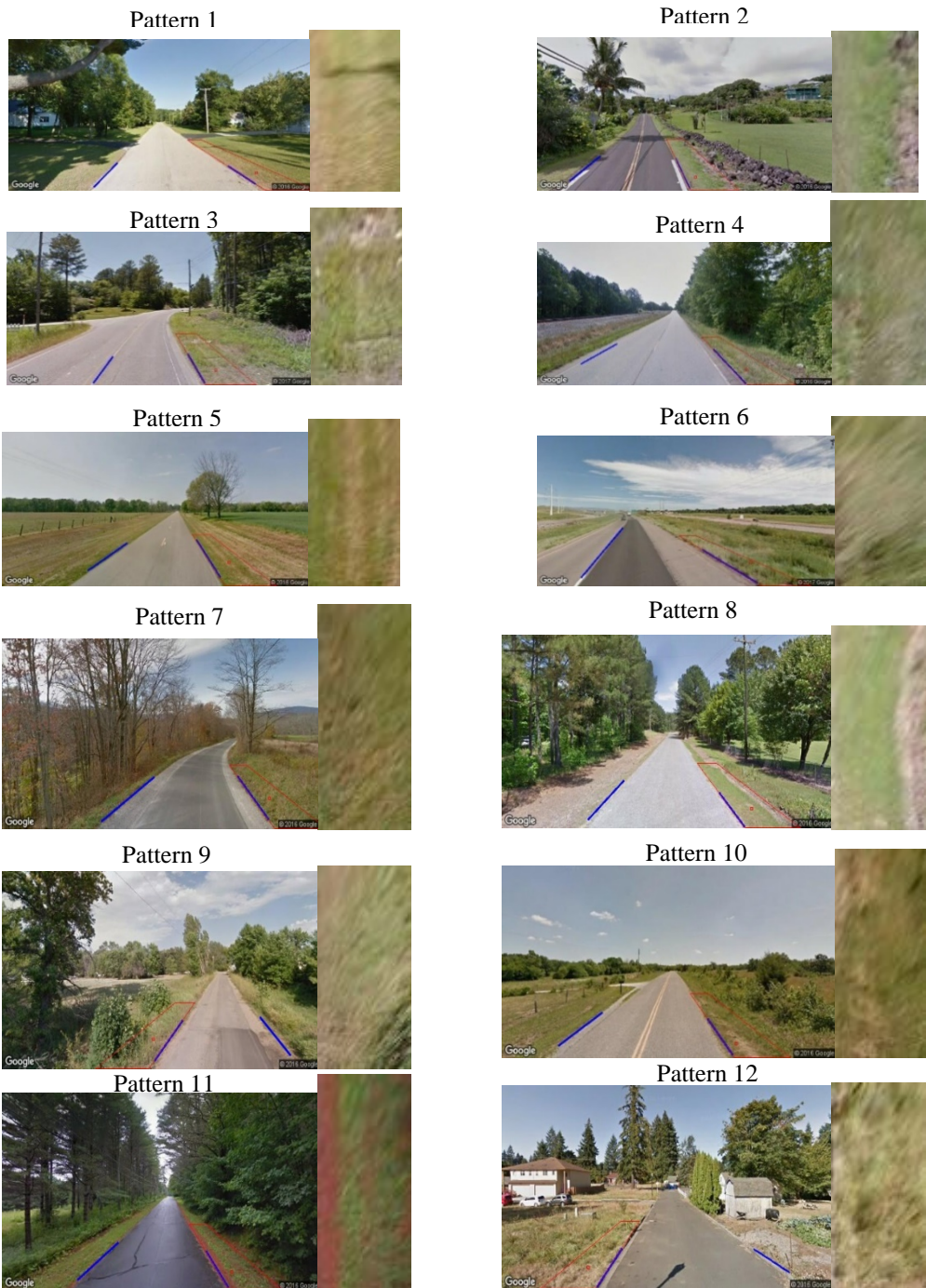




Fig. 9. Grass color patterns.

Radar Characteristics of Representative Grass

24GHz RCS and 77GHz RCS were measured on three grass samples. The physical appearance of these grass samples is shown in Table 2. The radar set up is illustrated in Fig. 10. The maximum, minimum, average and mean 77GHz RCS measurement result of these grass samples are in Fig. 11. The maximum, minimum, average and mean 24GHz RCS measurement result of these grass samples are in Fig. 12. The x-axis of the plot is the distance of the grass to the radar. The Y-axis is the RCS value. The blue vertical line indicates the location of the reference corner reflector. The RCS on the left of the vertical blue line is heavily influenced by antenna coupling and is not useful. The RCS on the right side of the dashed box is too weak and can be considered as background noise. The slope of the RCS plot in the region covered by the dashed box illustrates the RCS characteristics of the grass.

Table 2.
Grass samples used to measure 77GHz RCS.

Grass	Height	Color	Surface Condition	Type
1	Short (2-4 inches)	Green and Yellow	Somewhat even	Wild
2	Medium (8-10 inches)	Green and Yellow	Uneven	Wild
3	Short (2-4 inches)	Green	Very even	Well maintained

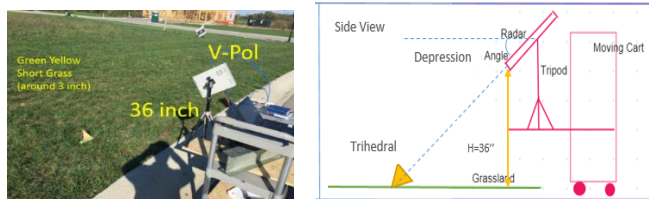


Fig. 10. Grass 77GHz RCS measurement.

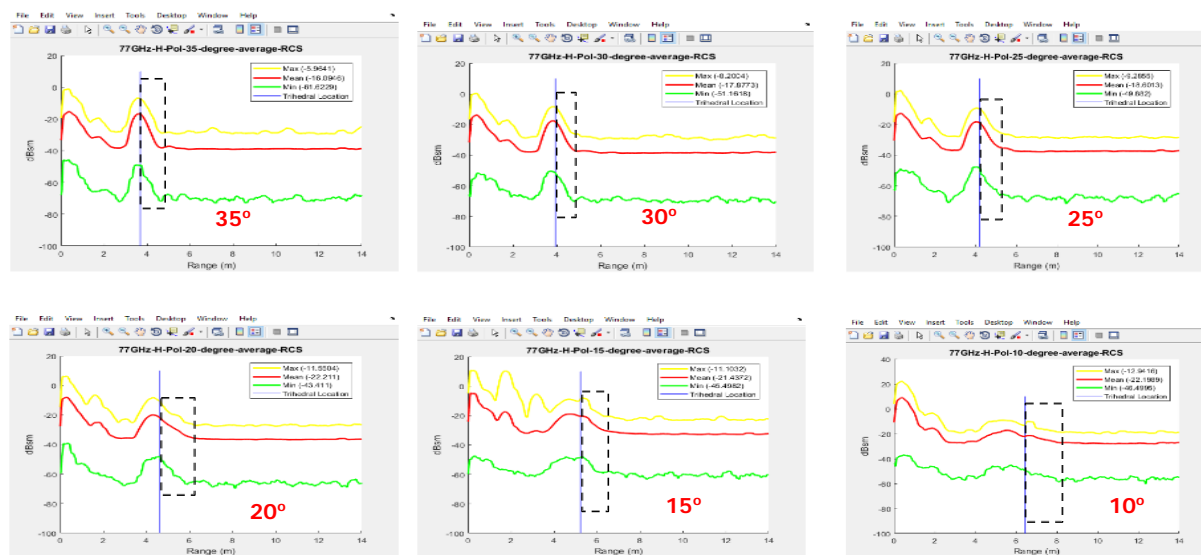


Fig. 11. Grass RCS Recommendation (77GHz Horizontal Polarization).

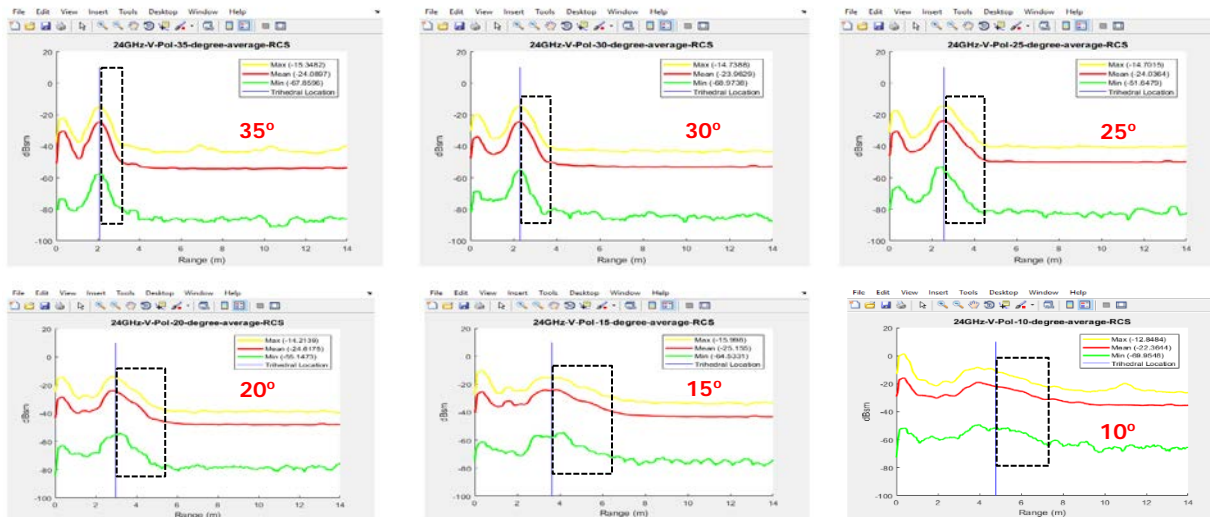


Fig. 12. Grass RCS Recommendation (24GHz Horizontal Polarization).

LIDAR Characteristics of Representative Grass

A spectrometer that covers a large range of light wavelengths was used to measure the diffusive reflectivity of 6 grass samples in indoor and outdoor at a range of viewing angles. The light source and the

measurement probe were placed as close as possible and aimed in the same direction to mimic the LIDAR operation. Multiple points were measured on each sample. Fig. 13 shows the upper and lower boundaries of all measurements at various angles, where 0 degree means that the LIDAR beam is perpendicular to the surface being measured. The upper bound is the measured maximum IR reflectivity value plus 0.05 and the lower bound is the measured minimum IR reflectivity value minus 0.05. It can be seen that the IR reflectivity of the grass increases as the viewing angle is getting further away from the perpendicular direction. The grass starts to show specular reflectivity when the measurement angle is above 50 degrees. The IR reflectivity also increases as the infrared wavelength increases in the 800-1100nm range.

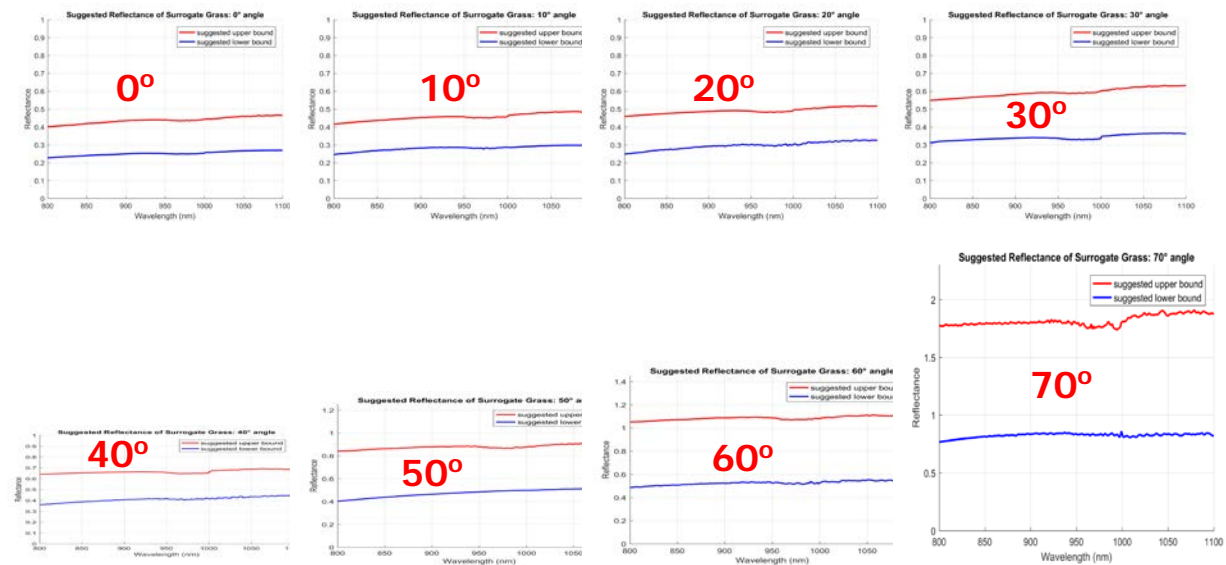


Fig. 13. The IR reflectance of grass fields at various measurement angles.

CONCLUSIONS

This paper summarized the 77GHz and 24GHz radar, LIDAR, and camera characteristics of grass, metal guardrail, and concrete divider. This information can be used for the development of grass, concrete divider, and the metal guardrail surrogates, which is essential for the standard evaluation of the Road Departure Warning and Road Keep Assistant systems. Based on this information, we have already developed surrogate grass, guardrail and concrete divider for testing. The design and testing of the surrogates will be described in future publications.

ACKNOWLEDGMENT

This research was sponsored by the Toyota Collaborative Safety Research Center.

REFERENCES

- [1] "Roadway Departure Safety," U.S. Department of Transportation Federal Highway Administration. https://safety.fhwa.dot.gov/roadway_dept/.
- [2] Arora, Prashant, David Corbin, and Sean N. Brennan. "Variable-sensitivity road departure warning system based on static, mapped, near-road threats." In Intelligent Vehicles Symposium (IV), 2016 IEEE, pp. 1217-1223. IEEE, 2016.
- [3] Lattke, Benedikt, Alfred Eckert, Harald Feifel, Dominik Fröhlich, J. Mccai, Ganesh Adireddy, Florian Janda, and Erich Fuchs. "Road departure protection-a means for increasing driving safety beyond road limits." In 24th International Technical Conference on the Enhanced Safety of Vehicles (ESV), no. 15-0212. 2015.
- [4] Harry W. Taylor, "Preventing Roadway Departures," US Department of Transportation Federal Highway Administration. <https://www.fhwa.dot.gov/publications/publicroads/05jul/03.cfm>.

- [5] Charles F. McDevitt, "Basics of Concrete Barriers," *Public Roads Magazine*, <https://www.fhwa.dot.gov/publications/publicroads/00marapr/concrete.cfm>.
- [6] Sparbert, Jan, Klaus Dietmayer, and Daniel Streller. "Lane detection and street type classification using laser range images." In *Intelligent Transportation Systems*, 2001. Proceedings. 2001 IEEE, pp. 454-459. IEEE, 2001.
- [7] Kirchner, Alexander, and Th Heinrich. "Model-based detection of road boundaries with a laser scanner." (1998).
- [8] Cramer, Heiko, and Gerd Wanielik. "Road border detection and tracking in non-cooperative areas with a laser radar system." In *Proceedings of German Radar Symposium*, pp. 24-29. Bonn, Germany, 2002.
- [9] Fardi, Basel, Ullrich Scheunert, Heiko Cramer, and Gerd Wanielik. "Multi-modal detection and parameter-based tracking of road borders with a laser scanner." In *Intelligent Vehicles Symposium*, 2003. Proceedings. IEEE, pp. 95-99. IEEE, 2003.
- [10] Lakshmanan, Sridhar, and David Grimmer. "A deformable template approach to detecting straight edges in radar images." *IEEE Transactions on Pattern Analysis and Machine Intelligence* 18, no. 4 (1996): 438-443.
- [11] Kaliyaperumal, Kesav, Sridhar Lakshmanan, and Karl Kluge. "An algorithm for detecting roads and obstacles in radar images." *IEEE Transactions on Vehicular Technology* 50, no. 1 (2001): 170-182.
- [12] Ma, Bing, Sridhar Lakshmanan, and Alfred O. Hero. "Simultaneous detection of lane and pavement boundaries using model-based multisensor fusion." *IEEE Transactions on Intelligent Transportation Systems* 1, no. 3 (2000): 135-147.
- [13] Katzourakis, Diomidis I., Joost CF de Winter, Mohsen Alirezaei, Matteo Corno, and Reinder Happee, "Road-departure prevention in an emergency obstacle avoidance situation." *IEEE Transactions on Systems, Man, and Cybernetics: systems* 44, no. 5 (2014): 621-629.
- [14] Gupta, Rakesh, Ananth Ranganathan, and Jongwoo Lim, "Road departure warning system," U.S. Patent 9,077,958, issued July 7, 2015.
- [15] Dan Shen, Jun Lin, Stanley Chien, Qiang Yi, Renran Tian, Rini Sherony, "Important Roadside Features for the Development of Vehicle Road Keeping Assistance System," 2018 SAE World Congress, Detroit Michigan, April 2018.
- [16] FLH Standard Drawings, <https://flh.fhwa.dot.gov/resources/standard/Std617-11.pdf>,
- [17] Qiang Yi, Dan Shen, Jun Lin, Stanley Chien, Rini Sherony, "The color specification of surrogate roadside objects for the performance evaluation of roadway departure mitigation systems," 2018 SAE World Congress, Detroit Michigan, April 2018.

DEVELOPMENT OF TRAILER IDENTIFICATION SYSTEM FOR IMPLEMENTATION OF VEHICLE SAFETY COMMUNICATIONS IN ARTICULATED TRACTOR-TRAILERS

Alrik L. Svenson

National Highway Traffic Safety Administration
United States

Loren Stowe

Virginia Tech Transportation Institute
United States

Paper Number 19-0221

ABSTRACT

Develop and demonstrate methods by which a vehicle safety communications system on a heavy vehicle tractor can automatically determine the geometric parameters of the trailer being towed. This information is required to assemble a Basic Safety Message (BSM) that conveys the dynamically changing position of an articulated tractor-trailer combination vehicle to surrounding vehicles. A review of existing object-detection technologies and the means to extract the trailer parameters from these technologies was conducted. The classes of trailers with highest market penetration were identified and used in the development process of the trailer detection system so as to maximize the applicability to a majority of trailers on the road today. Using the required trailer descriptive parameters defined in the previous study, accuracy requirements were developed. These were derived based on the light vehicle requirements for Vehicle-to-Vehicle (V2V) communication specified in SAE J2945/1. Trailer-identification related data were collected using LiDAR (2D and 3D), radar, camera (monocular, stereo and thermal), and ultrasonic sensors. Subsequent evaluation of the data resulted in the selection of a subset of these technologies for development into a prototype system. The final system technologies included: camera (stereo and monocular), LiDAR (2D and 3D), and ultrasonic. The 3D LiDAR based measurement system developed was able to accurately detect and measure the trailer parameters for box and tanker style trailers which accounts for nearly 90 percent of the trailers in use on roadways in the United States. Also demonstrated were trailer identification solutions based on other technologies. The camera-based solution provided a less robust means than the 3D LiDAR while the ultrasonic and 2D LiDAR was found to be applicable for fixed axle trailers only. The system designs did not require any special trailer markings or input from the driver. In addition, a simpler alternative solution for some fleet applications was developed that utilized markings (AprilTags) placed on the trailer for identification. This research demonstrated that there were methods to determine trailer parameters automatically for use in vehicle safety communications systems on articulated heavy vehicles. The system developed in this study allowed for a sufficiently accurate representation of the position of tractor-trailers during turning maneuvers in the BSM. This is important for effective implementation of safety applications based on vehicle safety communications.

RESEARCH QUESTION / OBJECTIVES

Figure 1 shows a typical turning scenario. The solid purple represents the actual path of the truck and trailer and the grey shadowed area shows the position for the trailer in the light vehicle BSM. For the car in the left lane with no traffic ahead, this representation would communicate a vehicle ahead, resulting in a possible warning (false positive). The car in the right lane would be told there was greater distance between them and the trailer than actually exists and therefore may not receive a warning that should have been issued (false negative).

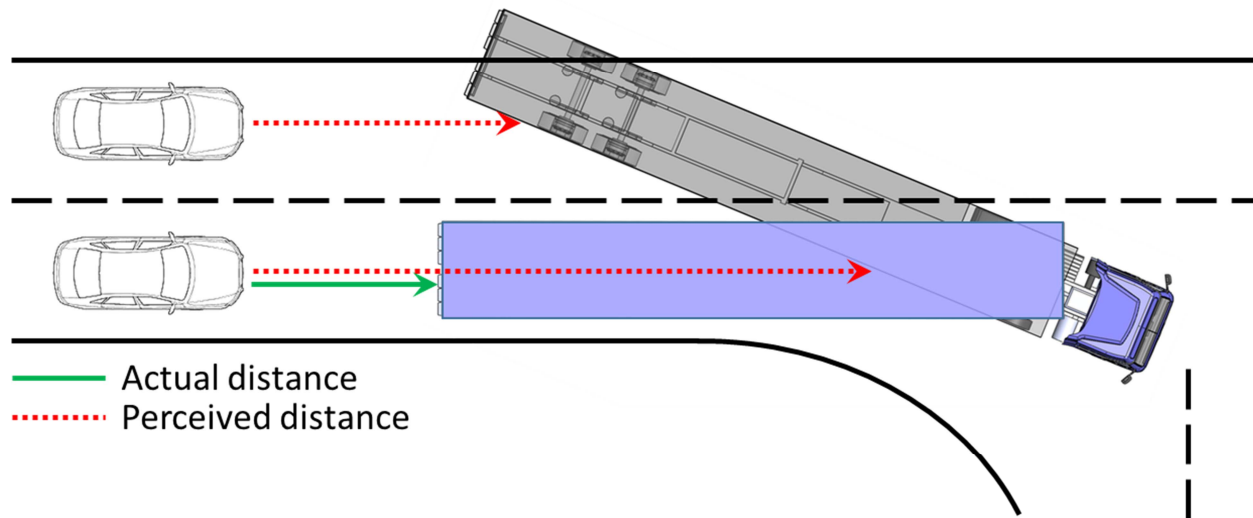


Figure 1. Single-body BSM Challenge for Articulated Vehicles During Low-Speed, Cornering

Previous research [1] showed that representing the trailer as a second vehicle was the most effective means of accurately representing the trailer to surrounding vehicles. Position and heading of the trailer was calculated based on the trailer geometry (length and pivot locations) and the kinematics of the tractor. A new data frame was proposed to transmit the information associated with the trailer.

The objective of this research was to develop and demonstrate methods by which a vehicle safety communications system on a heavy vehicle could automatically determine the trailer parameters needed to populate the content of the proposed Basic Safety Message (BSM).

METHOD

This project built on prior research which resulted in a proposed two-part BSM for heavy vehicle tractor-trailers [1]. The BSM developed in that study treats the trailer as a unique vehicle on the road during low-speed turning maneuvers. During these conditions, the system uses the trailer length and the two pivot locations (fifth-wheel and axle positions) along with the kinematics of the tractor to solve for the position and orientation of the trailer.

In order to develop a system to identify these three parameters, this research defined the scope of the project including the vehicle configurations and the target performance parameters the system needed to obtain. Then a technology survey was performed to identify applicable technologies for the system. These technologies were tested to determine which ones were most likely to meet the system requirements and then integrated into a test bed for evaluation. Based on this initial evaluation, the best performing sensors were selected for integration, testing, and demonstration.

CONSTRAINTS

Scope

One of the guiding principles of this research was that the final system was practicable for the trucking industry. Consequently, the scope of the project focused on the market segment that would impact the largest number of the tractor-trailers on the road. This kept the primary investigation to single trailer trucks, though the potential efficacy of the methods developed to work with multi-trailer heavy vehicles was included in the evaluation. Similarly, rather than trying to develop a solution that would work for all single-trailer truck configurations, including all the variations of load and trailer types, this research surveyed focused on the truck tractor market segment in the U.S. to ensure the development effort was applied toward the largest number of trailers currently on the road.

To accomplish this, annual trailer sales [2] were reviewed to provide an estimate of the trailers on the road. Functional categories were defined consistent with extracting the parameters pertinent to the project from sensor data. For example, box van presents a rectangular feature with straight lines that fall in a common plane. Similarly, container chassis and dump trailers present similar features. Consequently, these trailer types were grouped into the same class. The following list presents the categories shown in Table 1, which group types of trailers based on similarities in how the trailer parameters would be extracted from sensor data.

- Box = dry van + reefer + container chassis + dump
- Flatbed = flatbed + platform + low bed
- Tanker = tanks + dry bulk
- Other = those not included above

Table 1.
Distribution of Trailers Based on Annual Sales

Class	Box	Flatbed	Tanker (round)	Other
Number	285952	36787	15062	2147
Percent	84%	11%	4.5%	0.5%

Performance requirements

To set the performance requirements for the system, the operational conditions were considered along with the performance requirements of the V2V system as a whole. In particular, accuracy targets for length, axle position and 5th wheel or hitch position as they relate to the BSM elements of vehicles size, position and heading were determined.

SAE J2945/1 [3] provides system requirements for light vehicle, on-board V2V systems. This is currently the only published standard that provides function and performance requirements. It was therefore used as a starting place to identify minimum performance criteria for the trailer measurement system. Table 2 provides the requirements from SAE J2945/1 that were relevant to the trailer parameters.

Table 2.
Relevant SAE J2945/1 Requirements for Light Vehicles

Parameter	Value	Description	Primary Mapping to Heavy Vehicle
vPosAccuracy	1.5 m	2D position accuracy* of vehicle reference point	Axle location
vHeadAccuracyB	3 deg.	Heading accuracy* when speed is less than vHeadingSpeedThresh	Heading used to calculate other parameters
vHeadingSpeedThresh	45 km/h	Speed threshold for heading accuracy requirement	Relevant speed
vSizeAccuracy	0.2 m	Length and width accuracy requirements	Length

* Must be accurate to within the value of the vehicle's actual position or heading (respectively) for over 68 percent of the test measurements in open sky conditions.

However, as these specifications are for light vehicles, they had to be translated into values that were pertinent for a heavy vehicle and specifically to the trailer parameters necessary for populating the values for the two-part BSM. For example, vPosAccuracy is the accuracy requirement for the positioning subsystem, which includes at a minimum a GNSS (Global Navigation Satellite System). The average light vehicle width is around 1.8 m (6 ft.) which, for a standard 3.7 m (12 ft.) lane width, provides lane level accuracy. To get lane level accuracy for a 2.6 m (8.5 ft.) wide tractor-trailer (TT) would require a positional accuracy closer to 1.1 m (3.6 ft.). Note that this is trying to meet the intent of the current standard for lane level accuracy and is not under the constraints of the GNSS

performance. The 1.1 m value was then used as one of the parameters in the simulation model to determine the required accuracy for the pivot location. Table 3 provides a summary of the accuracy requirements for the measurement system.

Table 3.
Summary of Measurement Requirements

Parameter	Value	Comments
Length	≤ 0.5 m (20 in.)	Most common trailer lengths are > 2 ft. (0.61 m) different so the practical requirement is 1–2 ft. (0.3 - 0.61 m).
Axle position/ trailer wheelbase	1.3 m (52 in.)	Primarily effects lateral position of trailer during turning maneuvers.
5 th wheel/hitch location	< 1.1 m (43 in.)	Primarily effects longitude position but since this moves the pivot point on the tractor, it also changes the directional input for the trailer.
Angle	< 3 deg.	Used to derive pivot locations rather than provide heading.

SYSTEM DESIGN

Figure 2 shows a block diagram of the entire measurement system, including the components independent of the measurement subsystem being developed. On the left of the figure, different trailer types are listed. Those not greyed out were evaluated during the course of the study. The information path between the trailer and sensors is filtered through the environmental conditions that occur during normal operation of heavy vehicles. These include lighting conditions, weather (e.g., rain, snow, fog), road grime, site impurities (e.g., oil, grain dust), and anything else that could influence the quality of the data.

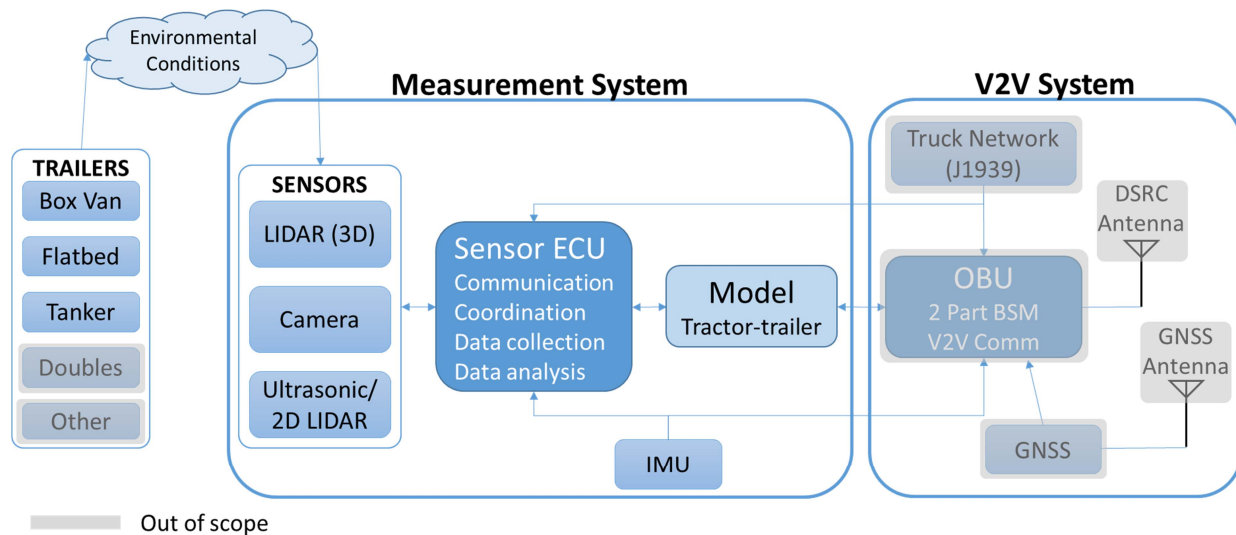


Figure 2. System Block Diagram

The effort for the system design focused on three primary components: the system software, sensors, and data processing. The system software resides on the sensor ECU and is responsible for the communication and coordination with the different system components, data collection from the different sensors, data storage, analysis of the data to extract the trailer parameters, and display of the information. System software and analysis methods will be discussed later in separate sections.

The sensors used in the study were evaluated on their ability to successfully address the different trailers and environmental conditions. For the initial evaluation, a wide array of sensors beyond what is shown in Figure 2 were examined. In addition to those that could measure the three trailer parameters, sensors that provided two or more distance measurements to the front of the trailer were evaluated. While this does not provide a measure of trailer length, for trailers with fixed axles at the rear of the trailer (e.g., tankers, bulk, dump), distance measurements along with tractor data required for the BSM allows calculation of the pivot locations (5th wheel and axle location). Trailer length could then be estimated by adding additional length to the effective axle location determined from trailer angle. This type of system could provide an alternative for trucking fleets that only haul fixed axle trailers and may be more appropriate for some environments. It may also require an additional step to tune the length factor based on the typical trailer within a fleet (e.g., fuel tankers). In addition to the trailer sensors, an IMU was included to provide truck data, in particular yaw.

Sensor Evaluation

In addition to collecting data with a heavy truck tractor and trailer, data were collected with a sensor suite at the Troutville weigh station on U.S. Interstate Route 88 (I-88) just east of Roanoke, VA. Data collection at different times of day starting at dawn and going to dusk was conducted to ensure a broad selection of lighting conditions. In addition to a stereo camera and LiDAR, two high-resolution digital SLR cameras were used to capture images at an angle and perpendicular to the trucks. Images from the latter provided a means to measure trailer length. A light gate was used to trigger the sensors as a truck entered the weigh station. This resulted in the collection of approximately 6,000 images on 2,000 different trucks. Of these, 5,000 were used in developing machine learning algorithms.

These data, along with the data collected on the tractor and trailer, were used in the sensor selection prior to the implementation. The following summarizes the results from the data collection performed during the system design effort. After that follows a description of the criteria used in creating the evaluation matrix that was assembled to help determine which sensor(s) would be used during implementation of the system concept.

Cameras The camera configurations tested during the system design performed as expected in most instances. Cameras are inherently sensitive to low light and low contrast conditions and this bore itself out in running classical machine vision techniques on the data. The trailer used in testing was white except at the rear where there was a collage of different images. This varied background often blended in with the surroundings. To address this fundamental challenge, optical flow was used to isolate pixels based on the motion of the trailer. Optical flow works by looking at consecutive frames and calculating the movement of pixels from one frame to the next. This provides an indication of the rear of the trailer as well as a means to identify pixels in the image associated with the trailer. These pixels can then be segmented into a single entity.

Figure 3 provides an example where the dark section of the end of the trailer looks like the yard and the building on the other side of the street and the street looks similar to the light portion of the trailer (first frame). Consequently, when a simple clustering is performed, the algorithm gets confused and lumps the street and the landscape in with the trailer (second frame). However, when the results from optical flow are used in conjunction with the clustering, the trailer is easily segmented out from the rest of the image (third frame).



Figure 3. Example of Trailer Blending in with Background

While this does not solve the problem of determining the trailer parameters, it does provide a means to extract the parameters.

In addition to having a relative motion that is different from the background, the trailer also has a predictable procession in the image through the turn. Figure 4 shows a sample of images taken during a turn. During the first half of the turn, the trailer moves from right to left in the image. Once it reaches the apex of the corner (lower left), the trailer starts to move left to right.



Figure 4. Procession of Trailer in Image during a Turn

By looking at the pixel velocities throughout the turn, the rear of the trailer can be identified. Figure 5 shows an example of this. In this analysis, the horizontal components of the pixel velocities were used. Red indicates pixels moving to the right and blue indicates pixels moving to the left in the image. The truck is past the apex of the corner so the trailer is moving back in line with the tractor, and thus is moving to the left. The black area above the trailer shows the boundaries of areas with different pixel velocities. The top of the trailer and the back of the trailer both appear as boundaries; however, the correct boundary is easy to identify given the relative strength of the lines and the fact there is only one vertical line.

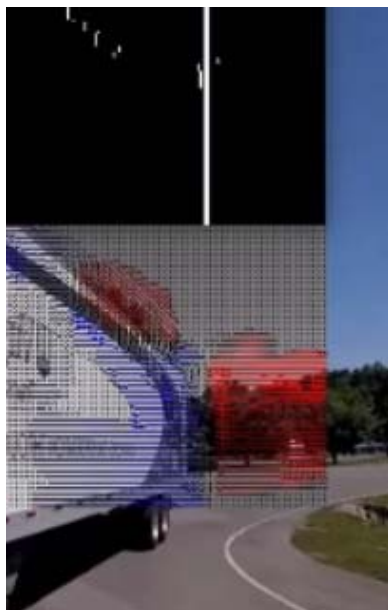


Figure 5. Identification of the End of the Trailer Using Optical Flow

As discussed previously, knowing the lateral position of the end of the trailer does not provide sufficient information to determine the length. However, with additional kinematic data from the truck or a sensor to measure angle, the length can be determined.

LiDAR The 3D LiDAR provided the most consistent results during the evaluation stage. The primary weakness was the cost. However, due to the push from automated vehicle development, the development of new, low cost units helped neutralize some of the cost considerations. 2D LiDAR provides a low cost alternative but does not provide sufficient data density to accurately determine length. The application of 2D LiDAR is therefore limited to trailer heading measurements.

Radar Two radar systems were evaluated. The first system was evaluated by the manufacturer of a light vehicle trailer length detection system. This system was designed to extend the functionality of a blind spot warning system when pulling a trailer, and automatically determines the length of the trailer rather than requiring the user to input the length. The system worked by picking up the motion of features of the trailer during a “significant/dynamic turning maneuver.” This information was then used to calculate the hitch to axle length of the trailer. The manufacturer performed additional testing to evaluate the effectiveness for heavy vehicles which revealed potential challenges to extending the technology to heavy vehicles. First, the motion of the trailer was slower with small trailers, making it more difficult to see the relative motion in the radar signature. Second, a large, flat, rectangular box van provided a poor reflective target for the radar. The expected outcome for the axle length measurement was < 1m standard deviation or 68 percent of the measurements would be within ± 1 m (± 3.3 ft.). Unfortunately, this was outside the acceptable accuracy for the BSM.

The second radar evaluation was set up to determine if a radar could identify the tires on the trailer. The hypothesis was that since the top and bottom of the tires are moving at equal but opposite directions, the relative velocity may be sufficient to be seen apart from the trailer. The first test performed was with the radar stationary as the truck drove past. With this configuration, the radar was able to pick up the tires on the trailer. However, when the radar was mounted to the tractor, the tires were no longer distinguishable.

While it may be possible to tune the signal processing of the radar data to extract trailer parameters, the amount of development that would be required was outside of the scope of the project.

IMPLEMENTATION

The primary sensors selected were 3D LiDAR, with the goal to improve the point cloud analysis and the single camera solution. For the latter, the stereo camera was used to collect the data so that both image sources were available for future development. Secondary sensors were the 2D sensor options of single plane LiDAR and ultrasonic sensors. Figure 6 shows the placement of the sensors on the tractor. The graphic is a simplified representation of the truck that was created to aid in the visualization of the real time data display. The sensor locations were based on the physical measurements of the actual tractor. The LiDAR was mounted at the top of the doorframe, the camera on the bottom of the passenger mirror, and the ultrasonic sensors and 2D LiDAR on the back of the cab.

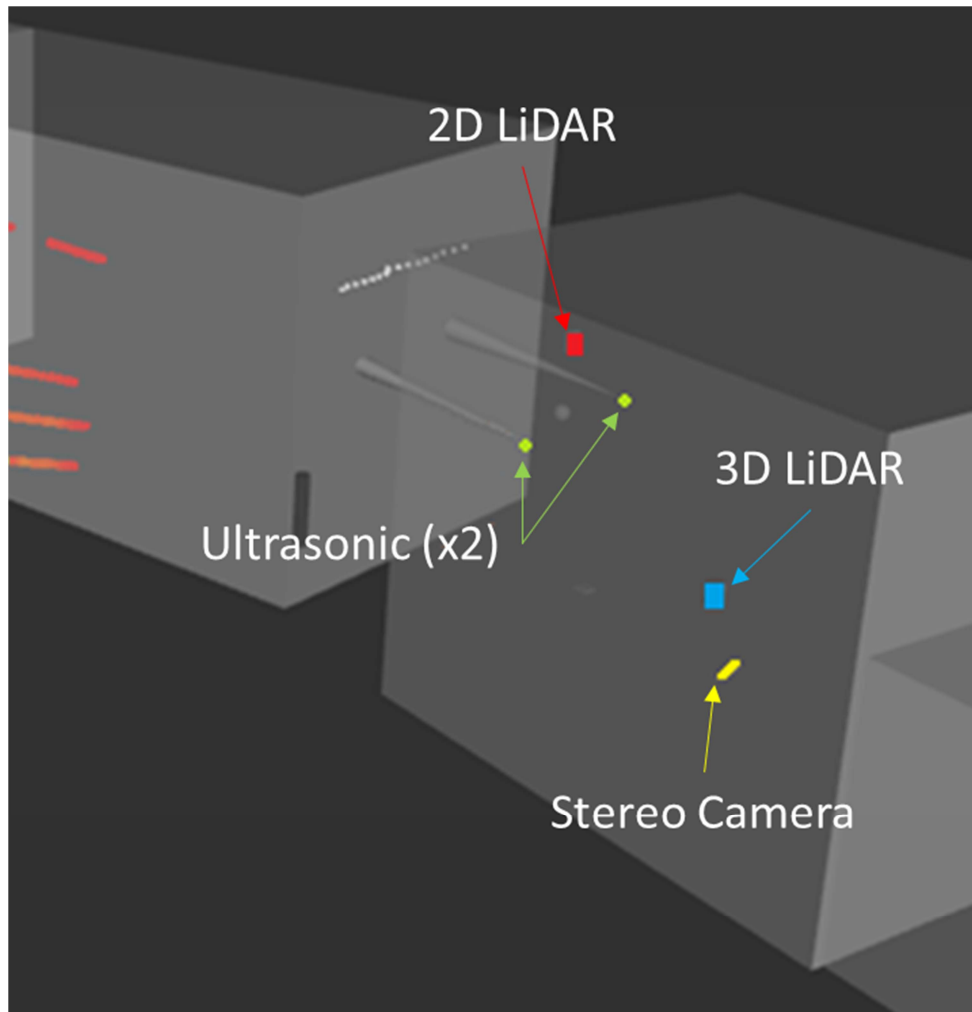


Figure 6. Sensor Placements on Tractor

All sensor data were displayed in real time. The 2D LiDAR output appeared as white dots on the front of the trailer, with each dot representing the output of one of the beams. Similarly, for the ultrasonic sensors, the output appeared as cones, which changed in length based on their returned values. For the stereo camera, both channels were recorded but only one of the video channels was displayed.

To demonstrate the functionality of the system as well as provide context to discuss specific development efforts, the flow diagram in Figure 7 shows the operation of the system and describes the solutions that were implemented. It should be noted that the system was designed as a proof of concept rather than a prototype of a commercial product. Consequently, some of the details were intentionally left out of the development. For instance, the first decision block evaluates whether the trailer is new or not. The most simplistic solution to this step is to assume a new trailer on start up. However, a more robust method might be to monitor the acceleration of the cab to identify the signature impulse that occurs when a tractor connects to a trailer. However, as this step does not preclude the demonstration of the measurement of the trailer parameters, the system was set to default to a new trailer on startup.

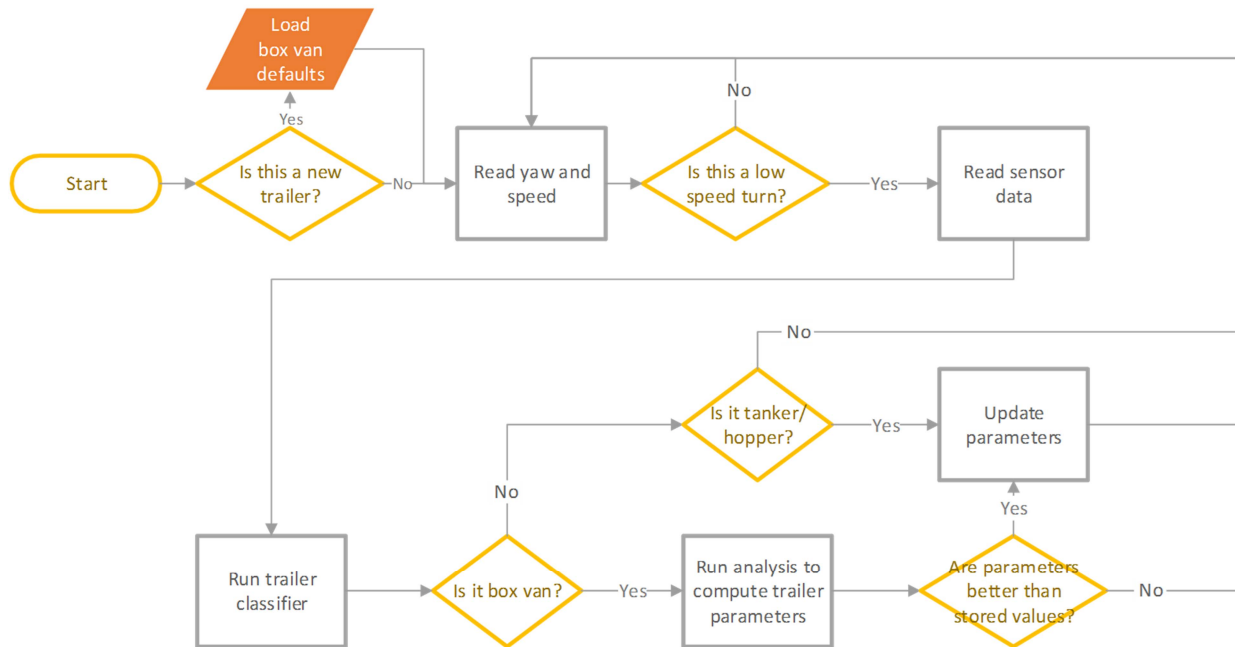


Figure 7. System Flow Diagram

Initialization

The first step in the algorithm is to initialize the system. As stated before, the default condition for this step is that the trailer is new. Therefore, the system initializes the trailer parameters with the following default values (Table 4) for a box van, as this is the most common type of trailer on the road.

Table 4.
Default Trailer Parameters

Trailer Parameter	Default Value	Comment
Length	53 ft.	The most common length of box van used is 53 ft., which is also the longest standard size. If this value is wrong, false rather than missed warnings will occur.
Axle position	0 ft. forward	This gives the trailer the longest wheel base possible, resulting in greater off-tracking.
5th wheel position	0 ft. (middle)	The midpoint minimizes the likelihood of exceeding the 1.1 m position error.

The system then monitors the yaw and speed of the tractor to determine if it is performing a low speed maneuver. Since the ECU was not tied into a V2V system nor the vehicle network, yaw was used. If yaw exceeds a threshold (0.2 rad), the next step was to read the data from the sensor suite.

The data from a single camera were used to run a trailer classifier to classify the trailer into one of four types: box van, tanker/hopper, double, or flat/other. The classifier was based on a convolutional neural network developed using the images from the data collection.

The output from the classifier directs the sensor data to the associated analysis module to extract the trailer parameters. The analysis for the other two trailer classes were not developed in this study, but the structure is in place to accommodate additional classes and associated analysis techniques.

Figure 8 provides a snapshot of the real time display collected during testing with different length trailers. The trailer in this example is a 45 ft. box van. The length displayed, which was extracted from the LiDAR data, is 44.81 ft. (13.66 m)

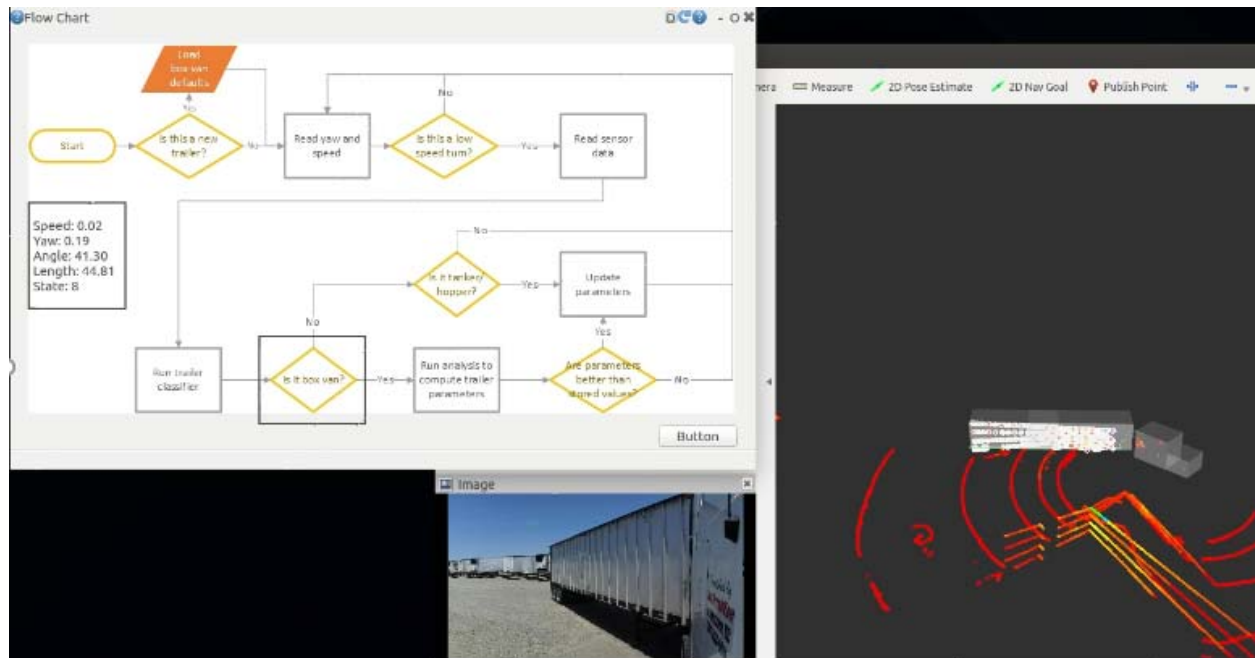


Figure 8. Example Output for 45 ft. Box Van

While the system collected the five sensor channels, the trailer parameter estimation for real time display was based on the point cloud data from the LiDAR. While the stereo vision camera can also produce point cloud data, the LiDAR provided cleaner data that yields better results. The single camera data were processed offline. While identification of the trailer is robust, determination of the trailer length consistently, turn after turn at the accuracy requirements identified, was a challenge. However, each turn provided an opportunity to collect more data and refine the trailer parameters if deemed appropriate.

Marked trailer Implementation

In order to demonstrate more than one solution, an alternative was developed that used special markings on the trailer. This option was included to determine the cost and benefit of this type of system over the type of non-contact system described previously.

One direct method evaluated for detecting the angle of the trailer used unique visual fiducial called AprilTags. Commonly used in augmented reality and robotics, these two-dimensional bar codes were easily detected by a camera system and directly provided pose. The pose information collected by the AprilTags included the X, Y, Z position and roll, pitch, yaw orientation parameters for each tag. Multiple AprilTags could be detected by a single camera because they each contained a unique pattern that corresponded to an identification number.

To track the pose of the trailer, a camera system was mounted on the rear of a heavy truck to observe the front of the attached trailer. An AprilTag fiducial was placed on the front of the trailer so that it could be continuously observed by the camera system during straight and turning maneuvers. A coordinate frame was established to correlate the camera's position to the detected fiducial at every timestamp. As the truck traversed straight paths and turns, the detected fiducial provided the pose information as an output. The most important pose parameter is the yaw angle, which directly correlates to the angle of the trailer relative to the camera. A more accurate measure of the trailer's angle from this extracted yaw angle required further transformations to the truck's axle or other defined coordinate frame. The tracked fiducial output was demonstrated on a closed test loop showing constant updates of the trailer's angle. The AprilTags were used due to their simplicity and existing software tools, but any picture or pattern can be

converted and calibrated into a fiducial for tracking by a camera system. Figure 9 provides an example of the application of the AprilTag, including the position of the tag and the results of the tag tracking.



Figure 9. Example of Output from AprilTags

The camera requirements were relatively low, so an inexpensive camera solution could be used. In addition, the method was robust in terms of placement of both the camera and the tags. One embodiment of this solution could be for a fleet to place these markers on their trailers. The code itself could be associated with a given length so that in addition to measuring the angle of the trailer, which provided heading as well as a means to determine pivot locations, the system would also know the length of the trailer from the marker. Another embodiment would provide drivers with a selection of tags that they would then place on the front of a trailer during hook up. They would be responsible for selecting the tag with the correct associated length.

While still being subject to the same weaknesses of other camera systems, this system provided a lower cost alternative to the fully automated system. The tradeoff is that it required more operator interaction to ensure the proper tag was on the trailer and that the tag was clean of debris. However, for small fleets or owner-operators, this tradeoff may allow these fleets to implement a more economical V2V solution.

RESULTS

Figure 10 shows a single frame of the output for 33 ft., 45 ft., and 53 ft. trailers. The return from the LiDAR data turned white when it identified the side of the trailer. The length of the trailer was then updated to reflect the length calculated from the data. The system was able to identify the trailer and extract its length and angle.

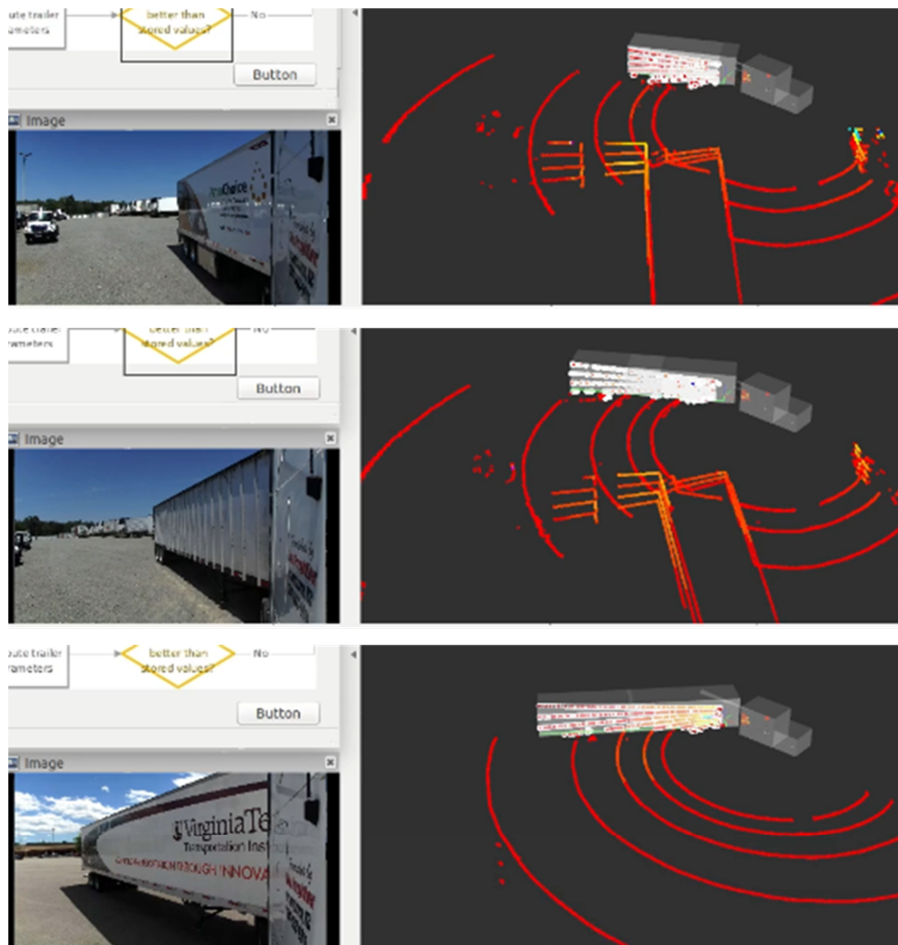


Figure 10. Display of Single Frame from System Output for 33 ft., 45 ft., and 53 ft. Trailers

The plots in Figure 11 show the results for a simple turn with a 53 ft. trailer. The lower value on the left plot, approximately 10 degrees, indicates the minimum angle that the system was able to extract from the trailer measurement data. The right plot shows the time for the measurement to settle in to its final value.

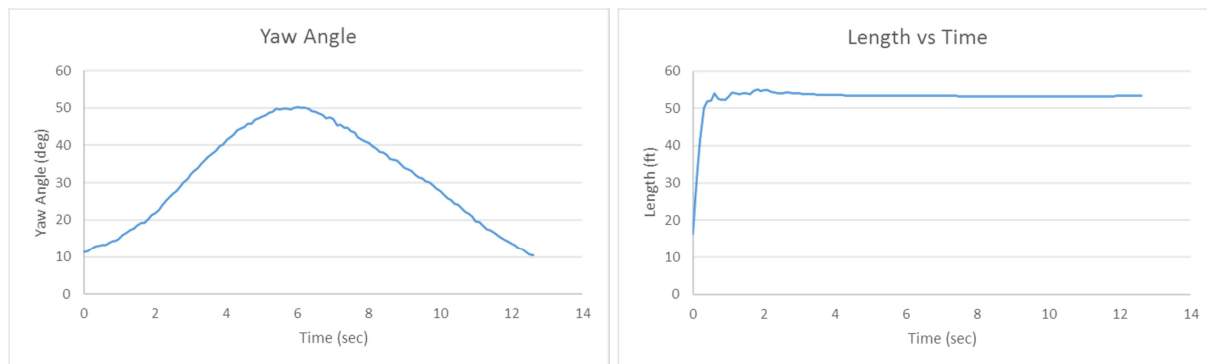


Figure 11. Length as a Function of Yaw Angle

Within a few seconds of a turn with a high enough trailer angle, the trailer length settles into the final value within a few seconds.

Figure 12 shows the results from the tanker trailer. In addition to the angle and length, the system state is shown below as an indication of when the system is and is not reading data from the sensor suite. The red lines indicate the length requirement from Table 3 as applied to this trailer.

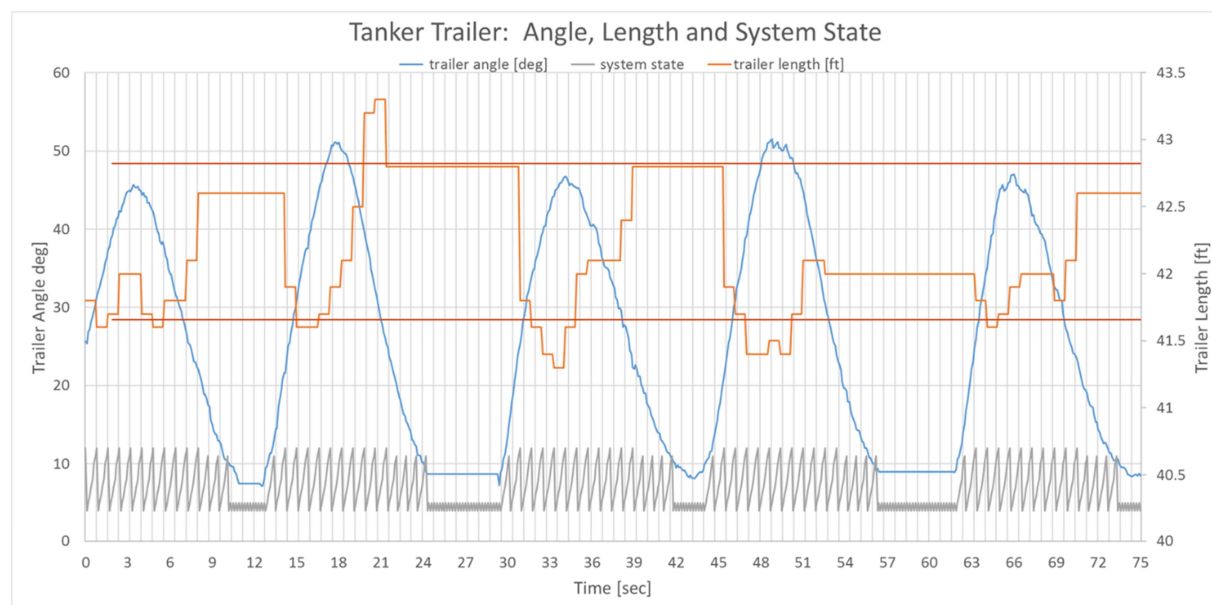


Figure 12. Trailer Length and Yaw Angle for Tanker Trailer

As expected, the tanker trailer results are noisier than for the box van. However, the system still provides adequate results for the BSM.

Results from the camera proved more challenging. The primary factors affecting the results were identification of the edges of the trailer, which were affected by lighting (e.g., shadows, low contrast, occlusions).

Based on a single frame from 45 turning events, with three different trailer lengths, approximately 50 percent of edge detections were within 2 ft. (0.61 m), 30 percent of edges were incorrectly identified, and 20 percent of detections were outside of the acceptable range. Applying the analysis to the entire video sequence during the turn and applying statistical analysis to reject outliers and provide an indication of the quality of the measurements would improve the performance of the method. In addition, given the method's sensitivity to changing light, it would provide a sample across a wider variety of lighting and backgrounds and therefore not be dependent on a single sample.

The ultrasonic, 2D LiDAR and the marked trailer solution (AprilTags) demonstrate solutions that can provide trailer heading information. However, trailer length would have to be obtained through a secondary method. For AprilTags or similar defined tag, trailer length can be associated with a given tag design. For flat trailer surfaces, the ultrasonic and 2D LiDAR perform similarly. While 2D LiDAR is more expensive than ultrasonic, the additional measurement points give additional data from which to calculate the heading. This allows for application with a variety of trailer types and over a large heading range. AprilTags require a human to mark the trailer prior to operation but does provide lower cost solution compared to 2D LiDAR that could be applied to many trailer categories.

DISCUSSION AND LIMITATIONS

While the 3D LiDAR sensors provided the best performing solution tested, they are currently comparatively high in cost. However, with the focus on future automated driving systems, the rapid development of new lower cost sensor solutions is occurring. Consequently, it is expected that cost effective LiDAR sensors could soon be available for use in heavy vehicle V2X applications.

The 2D sensors (ultrasonic and 2D LiDAR) and the marked trailer method provide three different potential solutions to provide trailer heading information. If trailer length is known through some other means, these lower cost alternatives demonstrated provided the opportunity to broaden the adoption of vehicle safety communications by trucking fleets that may otherwise choose not to integrate the technology. However, the lower cost AprilTags have the limitation that they require a human to mark the trailer prior to operation.

CONCLUSIONS

The study described in this paper developed a system that detected and measured the trailer parameters required for populating the elements of the 2-body BSM for box type trailers (dry vans, refrigerated, intermodal trailers, and other enclosed trailers) which account for over 80 percent of the trailers on U.S. roads. Table 5 provides a brief summary of the primary concepts developed and demonstrated.

Table 5.
Overview of Results for Primary System Concepts

Concept	Strengths	Weaknesses
3D LiDAR	<ul style="list-style-type: none"> Provides all three trailer parameters Robust measurements Works in low/no-light conditions Provides for other safety functionality (e.g. blind-spot warning) 	<ul style="list-style-type: none"> Requires significant turning maneuver (>10 degrees) Cost currently higher than other sensors
Camera (no trailer modification)	<ul style="list-style-type: none"> Provides all three trailer parameters Low cost Provides for other safety functionality (e.g. blind-spot warning) 	<ul style="list-style-type: none"> Requires significant turning maneuver (>10 degrees) Increased processing requirements Accuracy sensitive to lighting
Camera (with trailer modification)	<ul style="list-style-type: none"> Provides all three trailer parameters Low cost Results for low turning angles Robust measurements 	<ul style="list-style-type: none"> Requires modification of trailer Sensitive to lighting No additional safety functionality

REFERENCES

- [1] Svenson, A. L., Peredo, G., & Delgrossi, L. (2015). Development of a Basic Safety Message for Tractor-Trailers for Vehicle-to-Vehicle Communications. In 24th International Technical Conference on the Enhanced Safety of Vehicles (ESV) (No. 15-0379).
- [2] Schenck, P. (2016, March 4). *2015 Trailer Production Figures Table*. Retrieved from Trailer Body Builders: <http://trailer-bodybuilders.com/trailer-output/2015-trailer-production-figures-table>.
- [3] Surface Vehicle Standard – On-Board System Requirements for V2V Safety Communications, SAE J2945/1, Warrendale, PA: Society of Automotive Engineers, March 2016.

DYNAMIC EVALUATION OF CLOUD-BASED ACTIVE SAFETY SYSTEMS

Gropengießer, Uwe

Maier, Christina

Kallweit, Dr. Roland

IAV GmbH

Germany

Paper Number 19-0306

ABSTRACT

The field of driver assistance systems faces new technologies like vehicle-to-x (V2X) communication [1] and cloud services to improve safety on the streets. These upcoming functions carry new possibilities and new challenges as well. Thanks to scaling-up techniques, it is already possible to gather and manage huge amounts of data in the cloud with less time consumption compared to standard systems. This data is suitable to be used for statistics and pattern recognition based functions with time-critical demands.

But beside the development of these functions there is always a need for evaluation to assure correct functionality. Therefore, IAV created a concept to dynamically evaluate cloud-based active safety systems like the wrong-way driver detection function developed by IAV, which is conceived to warn oncoming vehicles on motorways. This goal is achieved with cloud and V2X techniques.

The wrong-way driver warning is a service running on the cloud, which receives V2X messages from vehicles including their positioning data, heading and other information to reference their traces via map matching [2] algorithms. An underlying database compares the data with continuously calculated thresholds to recognize wrong-way drivers and warn others in the surrounding areas via V2X against them. As changing infrastructures like construction sites have an effect on the false-positive rate of the classification, it needs to be dynamically tested if the function is able to react appropriately.

For this reason we propose an approach for an evaluation process based on an integrated self-controlling module. This module notices changes in trajectories which can be caused by changed traffic guidance and adapts the detection parameters. As a result, the following detection should classify the vehicles correctly based on the changed conditions.

The discussed process of the introduced wrong-way driver warning shows an example how a specific cloud-based function can be dynamically evaluated without dependence on the functional logic. Especially functions whose results strongly depend on ever-changing input data need solutions to test their behavior in critical situations. This approach delivers also a possible answer how to implement additional methods to create more flexible and long-term reliable cloud-based active safety systems.

INTRODUCTION

With the possibilities offered by V2X communication and the opportunity to calculate models in the cloud, the field of predictive safety functions has experienced kind of a revolution. This is also a necessary development to fire progression towards autonomous driving. Therefore, research is driven to V2X and cloud-based functions to evaluate their potentials and limits [3]. There are also functions that dynamically adapt their algorithm parameters to changing inputs. These methods offer advantages and disadvantages, e.g. reacting to intraday situations but also learning algorithms incorrectly. One example of such a function is IAV's wrong-way driver warning which uses different information like vehicle positioning to detect wrong-way drivers on motorway junctions and warn endangered drivers nearby (Figure 1).

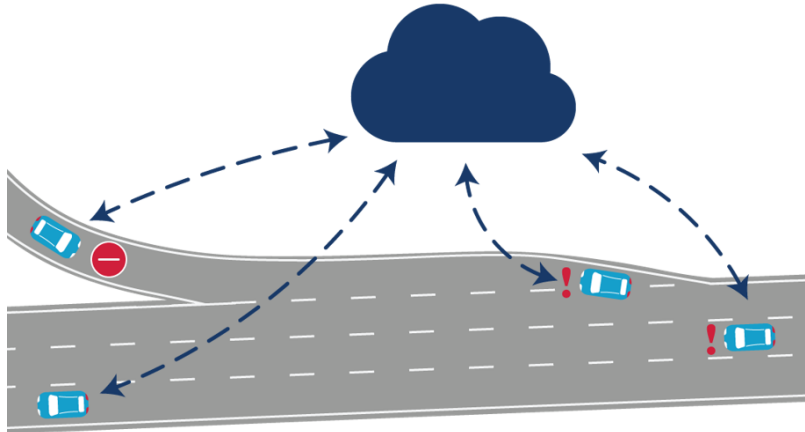


Figure 1. IAV's wrong-way driver warning function. In this figure you can see a possible scenario for the detection of a wrong-way driver and the need for the warning of the endangered drivers nearby.

According to given example, we present an algorithm that contains two different modes. The first mode is the training mode. In the first phase, data is collected to evaluate a motorway junction not yet trained by the algorithm. Among other things, the position data of the vehicles will be used to perform a map matching. A threshold value is searched, which indicates how far an object may move away from a map matched position, in order to avoid false-positives.

In the second phase, which is called "live" phase, the system allows to activate the detection of wrong-way driver for a given motorway or exit. In this phase every vehicle that drives this way will be evaluated. Whenever a vehicle exceeds the way specific threshold, the function warns the endangered drivers nearby.

This approach leads to the situation of handling position offsets regarding to e.g. daytime construction sites. Such scenarios can lead to the situation that the algorithm is not able to map match a vehicle or much worse to result in false-positives. In this paper we provide a method to calculate new thresholds while the live phase. The main goal is to avoid false-positives in any situation.

GPS BASED WRONG-WAY DRIVER DETECTION

Statistically speaking, the most validated incidents of wrong-way driving in Germany are caused by taking wrong entries at motorway junctions [4]. Therefore, we decided to observe the junctions regarding to the ramps and exits of the motorway. From this idea, we started to use the GPS tracking which is basically concentrated on such areas. To have a starting point we use a junction next to Ingolstadt. As you can see in Figure 2 there are four different ways to drive on this junction. Visualized GPS trajectories show their different traceable ways, which will be related to mapped roads.

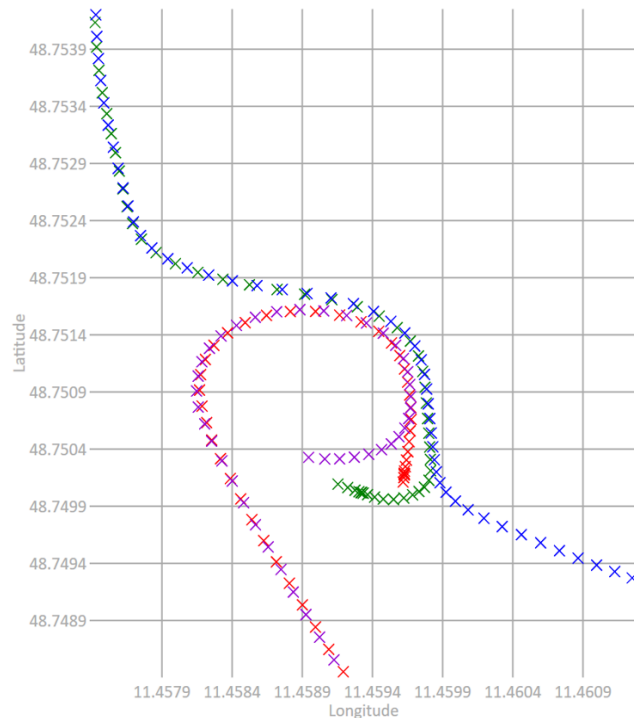


Figure 2. Measured GPS trajectories over time, based on real vehicle bus signals. As an example, this image illustrates four different GPS trajectories that describe the four different ways a vehicle can take on a motorway junction in Ingolstadt, Germany. This includes two motorway ramps (blue, green) and two motorway exits (red, purple).

Matching these trajectories on a map is needed to calculate thresholds for our wrong-way driver detection. This leads to the problem of map matching the vehicle to the correct road. The map matching process has to be done carefully, because GPS accuracy may vary and incorrect matches may influence the detection quality in a considerable way. To ensure that there is no false-positive, each motorway junction has a learning phase. Therefore, there is a need of doing different steps. Generally it is necessary to match each vehicle to the regarding road it takes. This is needed for the detection as well as for the warning part. This leads to the problem of map matching algorithms. In particular the algorithm has to handle the accuracy of GPS which has a potentially high variance. This can lead to incorrect matches. Therefore, the algorithm needs to calculate a threshold for each motorway junction and has to update the model in cycles. The thresholds are stored together with the map information like ways and prescribed driving direction in a database within the cloud. As described above, after the phase of learning the algorithm determines a threshold which is suitable for a given motorway junction and this way gets active for detecting wrong-way drivers.

When the live phase is released, the detection algorithm is running and warning endangered drivers (Figure 3). The detection is done by calculating probabilities. This probabilities are dependent on the positions over time, which are matched on the map information. The algorithm makes use of data from the database including the prescribed driving direction and compares them to the real vehicle driving direction, traceably by its GPS trajectory. If the probability is steadily increasing and moving into a danger area, a wrong-way driver will be detected and all endangered drivers nearby, as well as the wrong-way driver itself, will be warned via V2X messages. During the process of detection, the thresholds are still changing based on the input data from vehicles in order to provide flexibility to adapt to changing circumstances.

As mentioned in the introduction, daytime construction sites can lead to changed traffic guidance and sometimes lanes are closed or redirected over opposite lanes. This can result in false-positive detections, therefore

validation checked input data and a solution for handling changing infrastructures is advised. Otherwise the quality, robustness and durability of the function cannot be guaranteed.

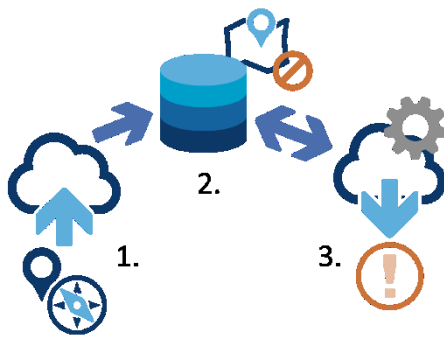


Figure 3. Productive wrong-way driver warning with dynamic adaption of detection parameters. In this illustration you see the processing steps of learning and warning of the wrong-way driver detection. In the first step the data is collected from the objects and sent to the cloud database. In the next step the data is map matched and compared with entries in the database for the detection algorithm. If a wrong-way driver is detected, the endangered drivers nearby and the wrong-way driver itself will be warned in step three.

This problem is not appearing exclusively at the described IAV wrong-way driver detection, but is also applicable to several other functions with dynamic behavior. To handle this problem, this paper introduces a solution concept and discusses the challenges and possible adaption to other functions.

IMPROVING THE APPROACH: DETECTING ALTERNATIVE WAYS AND RATE WAY VALIDITY

The already introduced wrong-way driver detection function uses map matching algorithms to relate the vehicle's trajectory to the map. The role of the used map database is essential, the function uses this as reference for the calculated thresholds as well as during map matching in the detection phase. But this dependency can have bad effects, like obsolete map data or temporary construction sites that is not considered nor recognized by the algorithm. This could lead either to false-positive detections or to no possible map matching, which in turn effects the productivity of the function. This lack of efficiency and reliability is not desirable for a safety function.

For this reason, solution concepts need to be developed to prevent from this effects. A conceivable approach for a self-controlling module could be the following described alternative way detection method.

This method takes up the theory that the way information could be extended by an expiration date attribute. This attribute could be used to register the actuality and validity of each section of way from the map. Usually a motorway junction is used several times per day. This means that map matching should happen on each way or section of way regularly. Exceptions from this assumption are closed or redirected lanes using opposite lanes or temporary roads (Figure 4). Respecting this scenarios during detection, an algorithm to indicate possible new ways and register no longer used ways is considered.

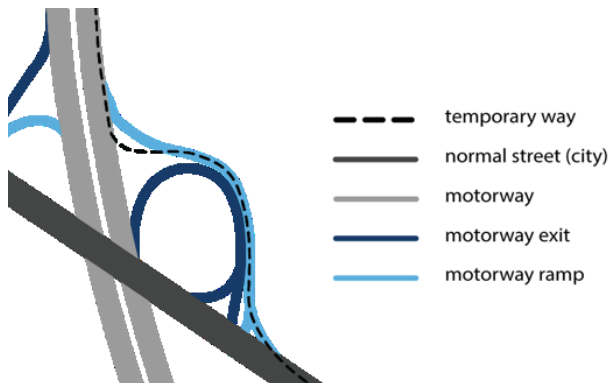


Figure 4. Example A for a temporary road due to construction site. The alternative way is following the motorway ramp excluding a specific section that leads to the motorway.

To detect such scenarios we need to classify each road within the database. The classification will have four different categories. We assume that the validation of the category increases with the usage of the road over time. Therefore, every way is classified by the categories seen in Figure 5.

If a way is indicated as used regularly, this is marked with the related expiration attribute and updated every time of map matching. Not regularly used ways and expired, not used ways can be detected by specific indicator rules or statistical calculations. During designing this indicators, it is important to consider seasons of the day and the amount of map matches over time. This is important, because overnight traffic volume is lower than during the day.

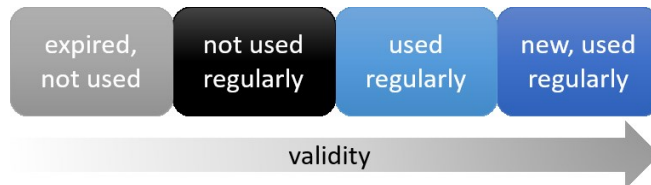


Figure 5. Classification scheme based on the validity of used ways. We provide a categorization of a way with four possible states. Expired means not used for a specific time, not used regularly has not been used for a specific time, used regularly is a normal used way and new, regularly used way is a validated alternative way.

Taking into account that already expired ways could also increase invalidity because of recently mapped trajectories, this ways are still stored in the database. From this point on they can also gain importance and be reactivated. Especially in scenarios of short-term closed or redirected routes this is a potential method to update the database without information loss.

Furthermore alternative ways, which are pretended as temporary roads, can have different characteristics. Basically they can be divided into three different types.

A. Ways that have common sections with already known ways

By their nature, there are different challenges in detecting sections as a potential new way. Caused by already known points, ways that have sections in common with ways in the database can be detected more precisely in general than completely unknown ways (Figure 4). It must be noted here that this statement is also dependent on how many sections or points are in common with already saved ways from database. In principle, the more points are common, the more certain is a successful and contemporary detection of an alternative branching way. This is based on the fact that already known sections are interpreted as validated and therefore they are weighted as more likely than unknown sections. Sections which are not known are not saved in the database and will be accepted with lower probability of existence. If trajectories are mapped to already known sections of ways and also describe new unknown ways, they are saved as possible alternative way, but not immediately as new and regularly used way. Only if this alternative way can be map matched frequently to appearing trajectories, thresholds are calculated and it will be marked as a new way.

B. Ways that have same start- and/or endpoints in common with already known ways

In cases of ways, which only have a common start- or endpoint (Figure 6) it is essential to know the covered way of a vehicle trajectory to get an indication of an alternative way. This means not only tracking motorway junctions but also trajectories before and after a known motorway junction. If the trajectories can be mapped to already known ways that are connected to a motorway junction, every successfully map matched point of the GPS position increases the probability of a plausible alternative way. This requires correct and reliable map matching without jumps in mapped ways, which means that the mapping process must not result in a variety of different possible ways. Otherwise map matching is unsteady and alternative way creation should be waived to prevent from erroneously applied ways and resulting false-positive detections of the wrong-way driver function. This suggested method requires information from additional ways that are connected to motorway junction and also need to be persisted in a database. To provide thresholds for map matching trajectories to additional ways, it is possible to use calculated average values from directly connected ways around, or they will be trained like the motorway junction way. If the alternative way is frequently map matched, the probability of a plausible alternative way increases every time of matching until it can be marked as new, regularly used way.

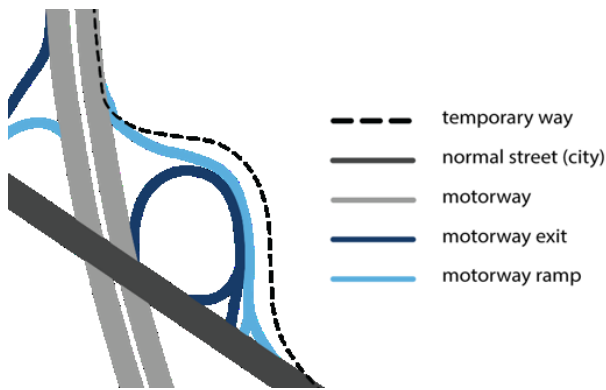


Figure 6. Example B for a temporary road due to construction site. The alternative way is next to the motorway ramp but ends up in the same point as the motorway ramp.

C. Completely new ways without common sections

Ways that have no point in common with any way from database only can be indicated by collecting trajectory information over a period of time (Figure 7). This also includes trajectories before and after motorway junction to detect where a way branches to another way that is not persisted in database. Indications are increased incidences of no further mapped positions at a specific position on the way. Every point of the unknown trajectory from the vehicle is insecure at the first time, so the probability of a plausible alternative way is low and increasing with every additional map matched trajectory from other vehicles. The required thresholds for map matching to the alternative way can be transferred from other known ways for the first times until they can be calculated individually. If an alternative way is considered, it must be handled with care, because the information about the correct driving direction is not validated by already known sections at this point. Therefore, only frequently occurrence of trajectories from vehicles in a certain time can be assumed as plausible and their driving direction interpreted as the correct driving direction. Every time of successful map matching to the alternative way increases the probability of plausibility, until the level is reached and specified as a new way in database.

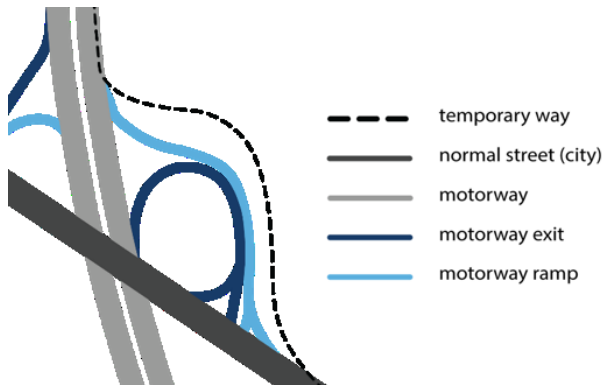


Figure 7. Example C for a temporary road due to construction site. The alternative way is next to the motorway ramp and has no point in common with it.

The described methods for detecting new ways on basis of already known ways require different additional information and have their limits. To get a first idea, if the described method is an applicable solution approach for the mentioned problem, exemplary tests were carried out.

EXEMPLARY TESTS

To prove the general functionality of the method, a first test set is used. This set includes an exemplary database with ways and thresholds for a simple motorway ramp (Figure 4). For each type of alternative way (A, B, C) a manually created artificial trajectory is used for testing. Therefore, a test trajectory is created which has no point in common with the motorway ramp (C), one that has the same startpoint and no other common sections (B), and another that has a section in common and a section apart from the motorway ramp (A). It is necessary that the section apart from the motorway ramp is not included in any threshold from the database, to prevent from map matching to existing ways. In this test environment the following mentioned values are assumptions and variably adaptable.

Because of the need for a frequently occurrence of the trajectories, each of the artificial trajectories is taken as basis to create 10 additional trajectories with a randomized deviation for each point respecting a maximum deviation of $5 \cdot 10^{-6}$ degrees in longitude and latitude. These trajectories serve as a test set to analyze the behavior of the algorithm to detect new ways.

Each point of the trajectory that is map matched to an existing way is rated with a percentage of 5%. This value is added to the general probability of existence of the alternative way. The expiring of ways is not considered in the test environment. Trajectories with GPS points that could not be map matched to existing ways, will be reserved as potential alternative way to compare them with new incoming trajectories. The next time a trajectory can be map matched to the potential alternative way, each GPS point is rated with a percentage of 0.5%, if it happens in less than a minute, the probability of existence assumes to be higher and the percentage is rated with 1%. In this test environment we suppose day time, so usually ways should be taken frequently.

If a potential alternative way is rated with at least a percentage of 90% it is considered as a new, regularly used way. If a way is not used, the percentage decreases every five minutes about 5%. The wrong-way driver detection algorithm only uses validated categories of ways (Figure 5) and no potential alternative ways.

With this parameterization the test environment is operated. For each categorized artificial trajectory every 30 seconds one of the randomized trajectories serves as input for the wrong-way driver detection function. After that, one of the trajectories is inverted to simulate a wrong-way driver and proof, if this is correctly detected. This procedure is repeated for each trajectory, so that for each category and each generated trajectory one inverted trajectory has been processed by the wrong-way driver detection.

RESULTS

During the tests we discovered that the process of map matching the changed traffic guidance to the already stored ways has to be done consciously. Failures during this steps can lead to bad influences on the detection algorithm, therefore a high specificity is required. In general, trajectories of category B and C could not constantly be detected as new ways caused by the problem of map matching and parametrization. Depending on the different categorized trajectories, the trajectories of type (A) has been detected earlier than for type B or C. This is an expected result, because of the common section to already existing ways in the database. The percentage of 0.5% or 1% for points that cannot be map matched to existing ways has been too low to reach the 90% level in some cases. When new ways have been identified correctly, and the map matching of the points to the new ways succeeded, the inverted trajectories have been detected successfully as wrong-way driver. The same applies to not inverted trajectories, which have been detected as driving in the correct direction.

Generally speaking, the regulation which defines the way when and how strong the changed conditions affect the database has to be defined by the amount and time intervals of their occurrence. Under these conditions we achieved higher quality rates than without the self-controlling module. When the map matching failed, the amount of false positives increases in some cases.

LIMITATIONS

The described evaluation process is limited to handling changed traffic guidance which is temporary not considered in the map. Depending on the parametrization of map matching the results of the evaluation process vary in both directions. In general this process enables to react automatically to changing street conditions and test the resulting behavior of the detection algorithm. But there are limitations.

Changed infrastructure directly on motorways is not considered. Furthermore, to build up a reliable self-controlling module it is advised and partly necessary to extend the database with connected ways around motorway junction ways, especially for completely new ways, which correspond to a new motorway junction. It is also necessary to respect the fact that motorway junction ways can have various forms, which are not further discussed in this paper, nor tested.

The introduced approach is mainly tailored to IAV's wrong-way driver detection, but also has adaptable aspects. For example, going one step back and gather additional information to indicate changes to react appropriately can also be adapted to other functions. Also the discussed classification scheme of ways is build up dynamically and not determined for a special defined function. The concept behind is extendable and open for changes.

CONCLUSIONS

The discussed process of the introduced wrong-way driver warning shows an example how a specific cloud-based function can be dynamically evaluated without dependence on the functional logic. Especially functions whose results strongly depend on ever-changing input data need solutions to test their behavior in critical situations. This approach delivers also a possible answer how to implement additional methods to create more flexible and long-term reliable cloud-based active safety systems.

REFERENCES

- [1] (in german). Fuchs, H., Hofmann, F., Löhr, H., & Schaaf, G. (2015). Car-2-X. In Handbuch Fahrerassistenzsysteme (pp. 525-540). Springer Vieweg, Wiesbaden.
- [2] (in german). Kartengestützte Ortung. Retrieved February 28, 2019 from <https://www.iigs.uni-stuttgart.de/forschung/projekte/mapmatching/>
- [3] Ress, C., & Wiecker, M. (2016). Evaluating the Potential of V2X Communication for Road Safety and Efficiency. ATZ worldwide, 118(1), 16-21.
- [4] (in german). Gerlach, J. Univ.-Prof. Dr.-Ing., Seipel, S. Dipl.-Ing., & Leven, J. (2012). Falschfahrten auf Autobahnen – Langfassung [PDF file]. 52. Retrieved February 28, 2019 from https://www.bast.de/BAST_2017/DE/Verkehrstechnik/Publikationen/Download-Publikationen/Unterseiten/V-falschfahrten.html

ESTIMATION OF POTENTIAL SAFETY BENEFITS FOR PEDESTRIAN CRASH AVOIDANCE/MITIGATION SYSTEMS IN LIGHT VEHICLES

Mikio Yanagisawa

Philip Azeredo

Wassim Najm

Volpe National Transportation Systems Center
USA

Stephen Stasko

National Highway Traffic Safety Administration
USA

Paper Number 19-0227

ABSTRACT

This report presents and exercises a methodology to estimate the effectiveness and potential safety benefits of production pedestrian crash avoidance/mitigation systems. The analysis focuses on light vehicles moving forward and striking a pedestrian with the front of the vehicle in the first event of a crash without attempting any avoidance maneuver in two priority scenarios: 1) vehicle going straight and pedestrian crossing the roadway and 2) vehicle going straight and pedestrian in or adjacent to the roadway, stationary or moving with or against traffic. System effectiveness is estimated for crash avoidance and crash severity mitigation. Safety benefits are projected in terms of annual reductions in the number of police-reported vehicle-pedestrian crashes, fatal vehicle-pedestrian crashes, and injured pedestrians at Maximum Abbreviated Injury Scale 2-6 and 3-6 levels. The methodology relies on target baseline crashes obtained from the 2011 and 2012 General Estimates System and Fatality Analysis Reporting System crash databases, system performance data from characterization track tests, and basic kinematic computer simulation of vehicle-pedestrian conflicts.

INTRODUCTION

From 2007 to 2016, there have been 350,408 fatalities on public roadways according to the National Highway Traffic Safety Administration (NHTSA) Traffic Safety Facts [1]. Over the last few years, the increase in population, licensed drivers, registered vehicles, and vehicle miles travelled has led to a rising trend in police-reported (PR) crashes and fatal crashes [2]. Figure 1 shows the number of pedestrian fatalities during this timeframe, as well as an upward trend in pedestrian fatalities as a percentage of total roadway fatalities. This trend may be caused by a variety of factors. This paper investigates the use of pedestrian crash avoidance/mitigation (PCAM) systems and their potential to ameliorate this trend.

PCAM systems are vehicle-based, forward-looking pedestrian detection systems that alert drivers of potential vehicle-pedestrian crashes and/or apply automatic emergency braking (AEB) to prevent potential vehicle-pedestrian crashes. This paper focuses on crashes that involve light-vehicles (i.e., passenger cars, vans and minivans, sport utility vehicles, and light pickup trucks with gross vehicle weight rating under 10,000 pounds) moving forward, striking a pedestrian in the first event of the crash, and not attempting any avoidance action.

This paper describes and exercises a methodology to estimate potential safety benefits associated with PCAM systems in terms of crash avoidance and crash mitigation measures.

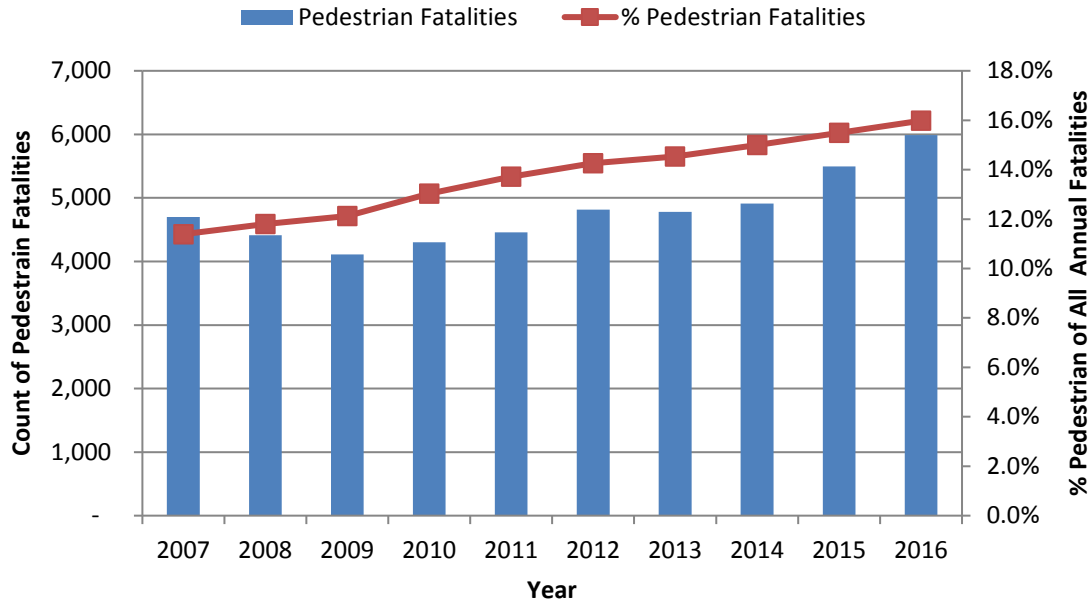
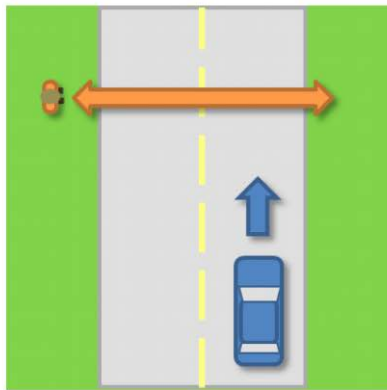


Figure 1. Annual Traffic-Way Pedestrian Fatalities in the United States.

Pedestrian Pre-Crash Scenarios

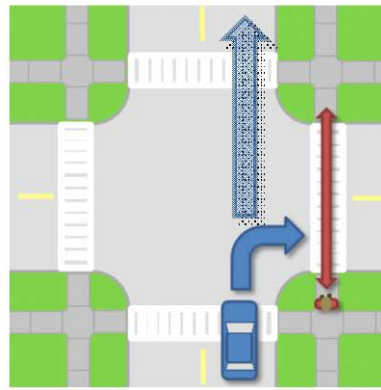
Historical research identified and prioritized vehicle-pedestrian pre-crash scenarios that PCAM systems could potentially address, and facilitated the development of test scenarios [3]. Four vehicle-pedestrian pre-crash scenarios were recommended as target scenarios based on the analysis of NHTSA's National Automotive Sampling System (NASS) General Estimates System (GES) and Fatality Analysis Reporting System (FARS) crash databases from 2005 through 2009 [4][5]. These four priority pre-crash scenarios are depicted and described in Figure 2. An updated analysis using 2011 and 2012 GES and FARS data provided similar results, giving evidence that the top priority vehicle-pedestrian pre-crash scenarios remained prominent from 2005 to 2012 [6].

From 2011 to 2012, there was an annual average of 62,917 vehicle-pedestrian PR crashes in the GES data that involved a light-vehicle striking a pedestrian in the first event. Based on similar criteria, FARS data provided an annual average of 3,337 fatal vehicle-pedestrian crashes. However, PCAM systems may only target a subset of these crashes. PCAM-addressable crashes involve the light vehicle moving forward and striking a pedestrian with the front of the vehicle and the driver attempting no avoidance maneuver. These criteria are selected because PCAM systems are considered forward facing vehicle-based sensing systems and driver action may significantly alter vehicle dynamics and system performance after the critical event (e.g., loss of control, unintended secondary events, and system suppression). As a result, the average annual number of all PR PCAM-addressable crashes amounts to about 21,000 crashes based on GES statistics, and about 2,200 annual fatal PCAM-addressable crashes from FARS data. The four priority pre-crash scenarios represent the most common vehicle-pedestrian crashes from 2011 to 2012, in terms of PR and fatal crash frequency as shown in Table 1. These four scenarios account for 90 percent of all GES and 97 percent of all FARS PCAM-addressable vehicle-pedestrian crashes. Thus, this paper focuses on the top four pre-crash scenarios as described by the previously published PCAM research (i.e., S1, S2, S3, and S4 in Figure 2).



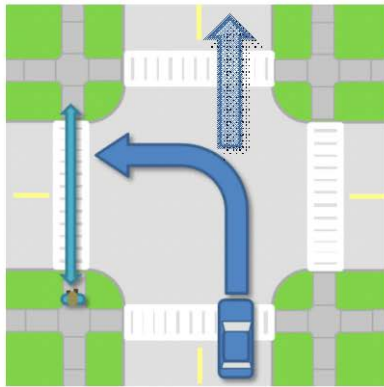
Scenario 1 (S1)

S1 - Vehicle going straight and pedestrian crossing the road



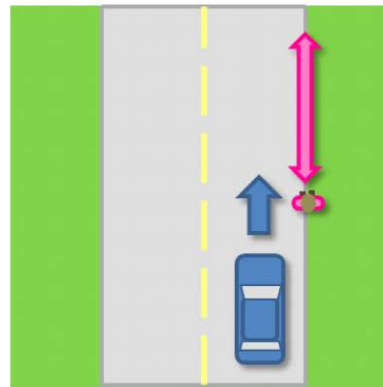
Scenario 2 (S2)

S2 - Vehicle turning right and pedestrian crossing the road



Scenario 3 (S3)

S3 - Vehicle turning left and pedestrian crossing the road



Scenario 4 (S4)

S4 - Vehicle going straight and pedestrian walking alongside the road with/or against traffic

Figure 2. Four Priority PCAM Pre-Crash Scenarios Defined from NHTSA Crash Databases.

Table 1.
Breakdown of PCAM-Addressable Crashes into Priority Pre-Crash Scenarios from 2011-2012.

Scenario	Vehicle Maneuver	Pedestrian Maneuver	GES Frequency		FARS Frequency	
S1	Going Straight	Crossing Roadway	7,481	35.5%	1,396	64%
S2	Turning Right	Crossing Roadway	2,264	10.7%	24	1%
S3	Turning Left	Crossing Roadway	6,200	29.4%	87	4%
S4	Going Straight	Walking along Roadway, with/against Traffic	2,950	14.0%	620	28%
Other Scenarios (~60 Additional)			2,195	10.4%	66	3%
Annual Average Total PCAM-Addressable			21,090		2,193	

*PCAM-addressable crashes are crashes involve a light-vehicle striking a pedestrian with the front of the vehicle in the 1st event of a crash, with no avoidance maneuver

Previous Research

Previous research studies have employed various methods on available data sources to estimate the efficacy of various advanced pedestrian safety systems, both active and passive. Two studies used the German In-Depth-Accident-Study (GIDAS) to estimate passive, active, and combination safety systems. The first study used GIDAS data to estimate the effectiveness of a 40-degree field of view (FOV) pedestrian AEB system [7]. A total of 243 pedestrian cases within a good FOV and no obstruction from the 1999-2003 GIDAS were identified. This study estimated new impact speeds based on variations in specific parameters to estimate the reduction in fatal and severely injured pedestrians. The duration of the braking event was a critical parameter variation. The average braking duration for drivers was 0.67 second, whereas the AEB system (≤ 0.6 g) had an average braking duration of 1.4 seconds. The results showed that the effectiveness at reducing fatally injured pedestrians in frontal collisions reached 40 percent, with a marginal increase in effectiveness with increased FOV. Nearly 80 percent of the fatality reduction came from cases where the driver had not braked. The second study estimated benefits of using passive (deployable airbag) and active (AEB) countermeasures to mitigate head injuries in pedestrian impacts [8]. This research used 68 GIDAS cases filtered for frontal impacts with pedestrians with severely injured heads. A series of equations and simulations estimated an average impact speed of 48.7 km/h (30.3 mph) in these target cases. Effectiveness estimates were presented for the active, passive, and integrated (active and passive) countermeasure systems. Results showed that the integrated system had an increased potential to reduce pedestrian head injuries as compared to either the active or passive system used alone. Effectiveness values ranged from 11 percent to 64 percent depending on the countermeasure parameters or the type of system modeled: active, passive, or integrated.

A major supplier for video sensing hardware and software used crash data from the Institute for Traffic Accident Research and Data Analysis (Japan) (ITARDA) to estimate the effectiveness of their product in vehicle-pedestrian crashes by identifying specific vehicles and their respective installation rate (none, version 1, or version 2) [9]. This empirical method did not provide explicit results, although basic calculations can provide crash avoidance effectiveness estimates derived from this work ranging from 75 to 88 percent. Furthermore, this study identified common reasons for deactivation based on US survey results, including: low sun angle (80%), followed by heavy precipitation (44%) and fog (17%).

A major car manufacturer used naturalistic driving data to describe pedestrian behavior, conduct track tests, and estimate crash avoidance rates [10]. The naturalistic driving data encompassed 110 vehicles that traveled 1.44 million miles in Indianapolis for one year. There were a total of 1,762 videos of potential conflicts with pedestrians. A distribution of time-to-collision (TTC) versus the number of cases was calculated and cumulative results showed a mean value of 4.43 seconds TTC when a vehicle-pedestrian conflict began. The lateral distances from the left and right side of the vehicle to the pedestrian (at the appearance point) were also calculated, showing means of 6.55 and 5.21 meters, respectively. Track tests of a vehicle equipped with a stereo camera and millimeter-wave radar showed variations in avoidance rate, based on scenario (e.g., pedestrian direction, vehicle motion, light condition, pedestrian size, and pedestrian motion). Preliminary results provided a wide range of effectiveness, including an avoidance rate of 84 percent when the vehicle was turning and an avoidance rate of 35 percent when the mannequin was darting (running).

The review of methods and results proved that a variety of potential data sources and methods may be used to estimate the effectiveness of PCAM systems. Further, as no two analyses are identical (e.g., variations in data sources, modeling, simulation, system algorithms), common elements were identified, including:

- Crash data: Understanding of the crash data provides valuable information, including pre-crash scenarios, initial conditions, and baseline measures.
- Harm curves: Derived from historical crash data to correlate impact speed to pedestrian injury. These curves help quantify benefits (e.g., crashes, fatalities, and injuries).
- Operational capabilities: Understanding the capability of the PCAM system can account for issues that arise when attempting to estimate system effectiveness, such as obstructions, bad weather, speed thresholds, and overall technological capability.
- Driver and system performance data: Incorporate driver performance (e.g., reaction time and braking level) and system performance (e.g., activation times, braking levels, driver-system interaction). Warning systems have different driver-system interactions compared to AEB, thus varying input data and modelling.

- Simulation or modelling (crash reconstruction or conflicts): A method to compare baseline results to treatment results, such as superimposing a PCAM system over historical crashes (reconstructed, probability of baseline crash = 1) or similar crashes in a simulation (probability of a baseline crash \neq 1). These can use hypothetical systems and conflicts when real-world crash data comparisons are not available.
- Crash avoidance and/or speed reduction: Results from baseline to treatment comparison to quantify system effectiveness and safety benefits for crash avoidance and pedestrian injury mitigation.

These elements are identified as core elements for the methodology, each requiring specific data sources and analysis.

APPROACH

The general methodology for estimating PCAM safety benefits is derived from a method previously used for vehicle-to-vehicle (V2V) based crash warning systems in support of NHTSA research efforts assessing the safety impact of V2V technology [11].

Basic Equations

A series of basic equations define the methodology, dictating a minimum set of data parameters. These data parameters determine what data sources can be incorporated into the methodology and further identify the need for basic assumptions.

Crash Avoidance The general equation of safety benefits and system effectiveness for crash avoidance is presented in Equation (1) [12].

$$B_A = N_C \times E_A \quad (1)$$

The equation provides a potential safety benefit for PCAM systems, in terms of the annual reduction of vehicle-pedestrian crashes avoided, B_A , based on the crash avoidance effectiveness, E_A , and annual number of target crashes addressed by a PCAM system, N_C . The crash avoidance effectiveness is broken down further, into two distinct ratios, as seen in Equation (2).

$$E_A = 1 - \frac{EM_{PCAM}}{EM_{Base}} \times \frac{CP_{PCAM}}{CP_{Base}} \quad (2)$$

The exposure measure, EM , refers to the probability that a vehicle enters into a vehicle-pedestrian conflict. The ratio, comparing with and without (EM_{PCAM} and EM_{Base} , respectively) will provide a positive safety benefit if vehicles are less likely to enter a vehicle-pedestrian conflict with a PCAM system compared to without any assistance. This measures the ability of a system to reduce the occurrence of conflicts in normal driving, typically derived from long-term naturalistic driving [13]. The crash probability, CP , refers to the probability that a collision occurs given that a vehicle-pedestrian conflict has been encountered. The ratio, comparing with and without (CP_{PCAM} and CP_{Base} , respectively) will provide a positive safety benefit if vehicles are less likely to strike a pedestrian with a PCAM system compared to without. This measures the ability of a PCAM system to reduce the likelihood of a crash, given that the vehicle has entered into a conflict [13]. Given the current state of data, minimal naturalistic driving and vehicle-pedestrian conflict (e.g., non-crash) data is available, making EM difficult to quantify. For this reason, it is assumed that vehicles would have the same exposure to vehicle-pedestrian conflicts whether or not a PCAM system is installed, neutralizing the EM ratio to 1. Furthermore, based on the state of the crash data, it is appropriate to use a crash reconstruction method, superimposing PCAM system performance on historical crashes. Using this method, the historical baseline crash rate is 1, as all conflicts resulted in a crash ($CP_{Base} = 1$). These assumptions simplify Equation (2) to Equation (3).

$$E_A = 1 - CP_{PCAM} \quad (3)$$

Based on the core elements defined earlier and the parameters identified within the equations, data needs have been relegated to crash data to determine target crash populations, N_C , and a baseline set of crashes to reconstruct, along

with human behavior and system performance data to determine the likelihood of a crash given system intervention, CP_{PCAM} .

Crash Mitigation In addition to crash avoidance, a PCAM system may potentially reduce any resulting harm to the pedestrian by reducing the vehicle's travel speed prior to impact through improved driver response or automatic vehicle control. Similar to Equation (1), the equation to estimate the reduction in pedestrian injury is provided in Equation (4).

$$B_M = N_I \times E_M = N_I \times \{E_A + E_W \times (1 - E_A)\} \quad (4)$$

The equation provides a potential safety benefit for PCAM systems in terms of the annual pedestrian injuries mitigated, B_M , based on the crash mitigation effectiveness, E_M , and annual number of pedestrians injured, N_I . Since any crash avoided would inherently avoid all subsequent pedestrian injuries, crash mitigation effectiveness, E_M , has to account for crash avoidance effectiveness, E_A , and assess the effectiveness of injury reduction, E_W , based on the resulting crash's impact speed. The method to estimate injury reduction effectiveness is shown in Equation (5).

$$E_W = 1 - \frac{H(PCAM)}{H(Base)} \quad (5)$$

The equation uses crash data to correlate impact speed and resulting pedestrian injury in a ratio comparing the pedestrian harm induced given a crash, with and without a PCAM system ($H(PCAM)$ and $H(Base)$, respectively). Given the above set of equations, crash data can be used to obtain additional information on the annual number of pedestrians injured, N_I , and to correlate impact speeds to pedestrian injury. Results from the crash reconstruction simulation can be used to determine impact speed with PCAM intervention.

Based on the above data parameters needed within the basic equations and the above core elements, the developed method is broken down into four key steps:

1. Identify and describe PCAM systems. This step identifies current and near-term production PCAM systems and describes their operational boundaries and capabilities. This includes operational design domain, countermeasure profiles, and driver-system interaction algorithms.
2. Identify data needs and data sources. This step uses the core elements to identify the priority data parameters and respective data sources, then performs a query and analyzes the data. This step assesses baseline conditions and treatment data (i.e., driver behavior with warning, system performance). Further, this step is setup to propose and execute a method to collect supplemental data, if feasible and necessary.
3. Run simulation and estimate effectiveness. Based on a preliminary assessment of the available data, it is appropriate that a crash reconstruction simulation, superimposing PCAM systems on historical crash cases, be used to estimate the effectiveness of PCAM systems.

PCAM SYSTEMS

A technology scan of public literature (e.g., media publications, owner's manuals, publicized testing) was used to understand the functionality and operational conditions of current and near-term production PCAM systems. The dynamics of a vehicle-pedestrian crash offer several intervention or countermeasure opportunities for PCAM systems. Table 2 shows the results of the technology scan of active PCAM systems. Since public literature was used, specific details on system capabilities and limitations were not available (e.g., warning suppression techniques, minimum and maximum thresholds for activation). The PCAM systems identified utilize various forms of technology. However the analysis conducted within this paper is independent of technological implementation.

Table 2.
Number of Active PCAM Systems (Current and Near-Term) Identified and Reviewed from Technology Scan.

PCAM System Type (Countermeasure Profile)	Warning Issued To		
	Driver	Pedestrian	No Warning
Warn Only	4	1	
Warn and Brake Assist	2		
Warn and Automatic Brake	3		
Brake Assist Only			1
Warn, Automatic Brake and/or Steer	2		

As noted earlier, the variations in countermeasures may require different data sets. For example, a warning to the driver would require system performance and driver response data, whereas an AEB-only system requires only system performance data. After assessing the various PCAM systems and associated driver-vehicle interactions, this analysis considers the potential safety benefits for the following three¹ PCAM systems:

- AEB only systems,
- Warning + first braking response between AEB or driver, and
- Warning + best braking response between AEB and driver.

Incremental benefits are determined by adding driver response to a warning issued prior to AEB activation. For example, a system would alert the driver, via warning, that a vehicle-pedestrian crash is imminent. This warning would elicit a driver response, but if a driver does not respond appropriately, AEB may initiate. This driver-vehicle interaction requires specific input data for the multiple components of the system. To encompass potential driver-vehicle interaction and system suppression methods, two logic systems are implemented when both driver and AEB are simultaneously activate:

- ***First Braking:*** Assumes that once braking has been initiated (by driver or AEB), it remains constant for the remainder of the event, regardless of magnitude. This assumes that any initial response suppresses secondary responses (i.e., driver is in control means no AEB is necessary, or AEB activation assumes the driver will never respond).
- ***Best Braking:*** Assumes that if both braking inputs are active (driver and AEB), the system uses the higher input to maximize braking effectiveness. If only one braking input is active (AEB or driver), then the system uses the active input. This system attempts to maximize effectiveness with the earliest and then the best braking response.

The driver-system interaction variations will provide a system effectiveness range, with the ‘AEB Only’ system providing a lower-limit range, while the addition of a warning to the driver may provide incremental benefits (as a driver may react earlier and/or brake harder than AEB).

DATA SOURCES

The next step of the methodology is to identify potential data sources for the necessary data parameters, then query and analyze these data sources. Within this step, if a data parameter could not be quantified from available data sources, additional data collection methods can be proposed and executed.

¹ Minimal information and data was found on the pedestrian warning and automatic steering countermeasure, therefore these countermeasures were excluded from this analysis.

National Crash Data

Historical crash data at the national level are available from NHTSA's GES and FARS crash databases. The GES provides a national representation of police-reported crashes in public traffic-ways, accumulating a sample of police-reports and incorporating associated variables into the data. The FARS provides a complete census of crashes on public roadways that resulted in a fatality within 30 days. These crash databases contain variables, codes, and relevant statistics that help to quantify and characterize the baseline pedestrian crash problem addressed by PCAM safety systems. The crash databases also contain details to specifically characterize each crash, including pre-crash scenario, travel speeds, environmental conditions, driver factors, and attempted avoidance maneuvers. Details surrounding the crash allow for an accurate depiction of the driving conflict, supporting a crash reconstruction simulation. PCAM-addressable crashes only include crashes where a forward moving light-vehicle struck a pedestrian with the front of the vehicle in the first event of the crash and the driver attempted no avoidance maneuver.

The PCAM-addressable criteria aim to encompass the operational capabilities of PCAM systems and their aimed effectiveness. Due to limited information on system performance with driver input (e.g., driver pressing the brake pedal may suppress AEB activation), attempted avoidance maneuvers were not considered. Impaired drivers may not react to a warning but an AEB component (if applicable) may be designed to still activate; therefore, impaired drivers were considered for this analysis. The following definitions were used to obtain the target baseline crashes:

- **Light-Vehicle:** The use of the vehicle body type variable in the crash databases identifies passenger cars, vans and minivans, sport utility vehicles, and light pickup trucks with gross vehicle weight rating less than 10,000 pounds.
- **Pedestrian:** Any person on foot, walking, running, jogging, hiking, standing still, sitting, or lying down, excluding any person on a personal conveyance such as personal mobility device or rideable toy.
- **First Event:** Crash data provide a series of critical events for the crash, regardless of injury or damage sustained (or lack thereof). The first listed critical event of the crash is considered.
- **Vehicle Moving Forward:** Crash data provide pre-event movement of the vehicle, prior to the driver's realization of an impending critical event. Movements listed as no driver, stopped, backing, parking related, or unknown are excluded.
- **Area of Impact:** Crash data provide the area of impact of the vehicle. Only crashes that identified the front of the vehicle to be struck (i.e., 11, 12, and 1 o'clock values) are considered.
- **Avoidance Maneuver:** Crash data provide the attempted avoidance maneuver of the vehicle in recognition of the critical pre-crash event. Only crashes with 'no avoidance maneuver' attempted by the vehicle are incorporated.

In addition to the statistics provided earlier in Table 1, these PCAM-addressable crashes resulted in approximately 13,000 injured persons at the Maximum Abbreviated Injury Scale (MAIS) 2+ levels and 7,000 injured pedestrians at MAIS 3+ levels. A conversion matrix was used to convert injury scales, from the GES KABCO injury into a MAIS injury [14]. Further, FARS is used to get the actual count of persons killed in target crashes and included in the KABCO-MAIS conversion. Table 3 shows the breakdown of these injuries into the priority pre-crash scenarios.

Table 3.
Breakdown of PCAM-Addressable Pedestrian Injuries into Priority Pre-Crash Scenarios from 2011-2012.

Scenario	Vehicle Maneuver	Pedestrian Maneuver	MAIS 2+	% of MAIS 2+	MAIS 3+	% of MAIS 3+
S1	Going Straight	Crossing Roadway	2,682	49.9%	1,879	56.9%
S2	Turning Right	Crossing Roadway	274	5.1%	92	2.8%
S3	Turning Left	Crossing Roadway	883	16.4%	333	10.1%
S4	Going Straight	Walking Along/Against Traffic	1,207	22.4%	860	26.0%
Other Scenarios (~60 Additional)			330	6.1%	141	4.3%
Total Injuries from PCAM-Addressable Crashes			5,376		3,305	

Injury Curves Injury probability curves aim to predict the probability of a pedestrian injury occurring given an impact speed. These curves are used to measure crash severity by correlating injury levels to impact speeds from historical crashes. Injury probability curves are derived from 2011 and 2012 GES and FARS data. Similar criteria as the above crash data are used, and the vehicle travel speed and resulting pedestrian injury are obtained to determine the injury probability for five-mph incremental speed bins.² It is important to note that travel speed information is mostly unavailable in the GES and FARS data where approximately 80 percent of crashes had unknown travel speed information. Results from this query are fed into a regression model to determine functions for the various harm curves. These smoothed curves from developed functions help mitigate anomalies found with smaller data sets and aid in eliminating unusual spikes in data. Figure 3 illustrates the results from the regression model.

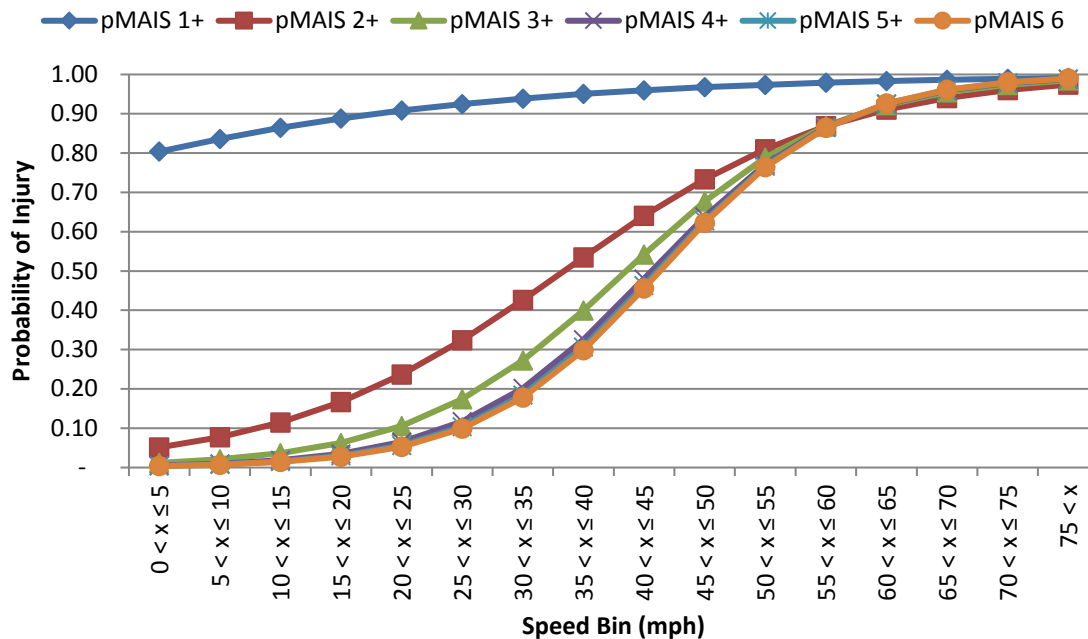


Figure 3. Plots of Pedestrian Injury Cumulative Probability Functions from Regression Model.

The probability for a certain injury level is simply the difference of two MAIS+ probabilities. For example, $p_{\text{MAIS}1} = p_{\text{MAIS}1+} - p_{\text{MAIS}2+}$ and $p_{\text{MAIS}2} = p_{\text{MAIS}2+} - p_{\text{MAIS}3+}$. The injury mitigation analysis in this report focuses on the MAIS 2+ and MAIS 3+ injury levels.

Special Crash Investigation

National crash databases contain an abundance of cases but lack detailed information on the dynamics of the crash. These databases rely on available police reports and witness statements to detail the pre-crash information (e.g., motions, speed, and critical events). Approximately three quarters of GES cases that could be addressed by PCAM systems do not have travel speed information (coded as ‘unknown’). Further, detailed information on the pedestrian motion is not readily available (e.g., left-to-right or right-to-left of the vehicle, when crossing the road). From the available information, accurate depictions of the crash become difficult, relying on multiple assumptions. A crucial missing element is the amount of time the pedestrian spent in view of the driver/vehicle, within the roadway, and in the vehicle’s intended path. One might assume, for maximum effectiveness, PCAM systems may attempt to maximize accuracy and responsiveness, while minimizing the number of nuisance and false activations. As part of

² Travel speed may not be equivalent to impact speed; and crash databases do not contain impact speed and have limited availability of travel speed. Travel speed is the vehicle’s speed prior to conflict and could be used if no attempt to avoid a crash was made.

the data identification task, a special crash investigation (SCI) team at NHTSA was tasked to investigate the detailed dynamics of an S1 scenario.³

The resulting database contains over 50 recorded variables for 43 relevant vehicle-pedestrian crashes where investigators were able to examine the crash in detail and estimate a comprehensive list of details that depict the exact kinematics of the crash. A list of variables obtained can be found in the Appendix. It is important to note that these 43 cases could not be incorporated into this methodology for numerous reasons (e.g., small sample size with wide range of results, bias towards severe injuries, not nationally representative). However, the data obtained provided detailed cases where PCAM systems could provide a benefit. The focus of the investigation was to determine TTC for the vehicle when the pedestrian was revealed to the driver (or would be PCAM system). Figure 4 details the TTC measure in a vehicle-pedestrian conflict.

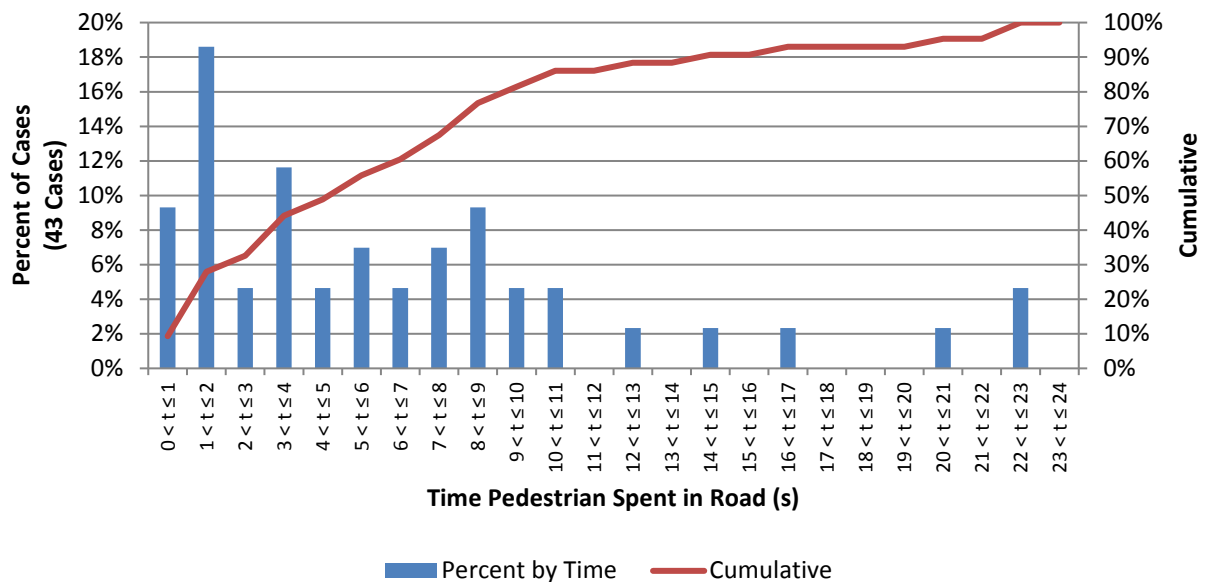


Figure 4. Distribution of Pedestrian Reveal TTC in S1 from SCI Database.

The information provides a wide TTC range, estimating a pedestrian being visible from under 1 second to as much as over 20 seconds. The majority of crashes had TTC values under 6 seconds, accounting for 55.8 percent of the crashes. Although the cases could not be used directly in the benefits model, the wide range signifies a potential for PCAM benefit. In cases with low TTC (less than 1 second), PCAM systems may have a difficult time detecting and identifying pedestrians, warning the driver, and/or applying AEB; this accounts for less than 10 percent of the cases. On the other end, in cases with a high TTC (greater than 6 seconds), PCAM systems may have ample time to detect, identify, and/or apply AEB, as this may be well beyond the longitudinal range of the technology used in PCAM systems. Furthermore, these cases identified drivers that were unable to detect, identify, and/or react to the conflict appropriately (e.g., distracted drivers, impaired drivers/pedestrians, or poor lighting conditions, dark pedestrian clothing). These drivers may potentially benefit from a warning, drawing attention to the pedestrian and aiding the driver in reacting appropriately.

Test Data

A crucial data source for estimating system effectiveness is system performance data. System performance data were obtained from characterization test runs conducted at the Transportation Research Center Inc. (TRC) in East Liberty, Ohio by NHTSA's Vehicle Research and Test Center (VRTC) [15]. Three production vehicles equipped

³ S1 was selected due to its potential variations on circumstances, high frequency, and injury rates. It is assumed in S4 that the pedestrian is already walking or standing in the vehicle's path, and therefore is limited by technological capabilities (e.g., a driver or PCAM system would be able to monitor an S4 situation as long as the pedestrian is within range).

with PCAM systems were tested in S1 and S4 priority pre-crash scenarios, varying multiple parameters (e.g., pedestrian size, pedestrian speed, pedestrian direction/orientation, lighting, obstructions, vehicle speed, and overlap).⁴ Vehicle speeds ranged from 15 to 45 mph. Detailed time-history data were collected for each test run and analyzed for 20 variables, including speeds, distances, warning activation time, AEB activation time, and resulting impact. After assessing the testing conditions and correlating respective testing conditions to crash data, the six distinct test scenarios shown in Table 4 were used for the benefits method. For other scenarios, since empirical test data could not be applied to crash data, system effectiveness was conservatively set to 0. This implies that PCAM systems would not have an immediate benefit. Further research, testing, and analysis would be required to revise this assumption.

Table 4.
Priority PCAM Testing Setups that Correlate to Crash Data and Associated Number of Test Runs and No Impact Results (All Vehicle Speeds* and Vehicles).

Name	Scenario	Pedestrian Size	Pedestrian Speed	Pedestrian Direction	Lighting	Obstruction	Number of Tests	'No Impact' Results
S1-A	S1	Adult	3.1 mph	Right-Left	Day	No	497	397
S1-B	S1	Adult	4.9 mph	Right-Left	Day	No	265	90
S1-C	S1	Child	3.1 mph	Right-Left	Day	No	194	167
S1-D	S1	Child	3.1 mph	Right-Left	Day	Yes	108	42
S4-A	S4	Adult	Stationary	Stationary	Day	No	403	325
S4-B	S4	Adult	3.1 mph	Away	Day	No	202	183

*Speeds ranged from 15 to 45 mph

Analysis of the resulting data provides characteristics of the various PCAM systems. Various parameters were analyzed, including correlating AEB activation time to vehicle speed and average AEB level to vehicle speed, as seen in Figure 5 and Figure 6, respectively. Each production vehicle was analyzed anonymously, labeled as original equipment manufacturer (OEM) 1 to 3. Additional parameters were analyzed for each of the six test scenarios and production vehicles to help in characterizing the system.

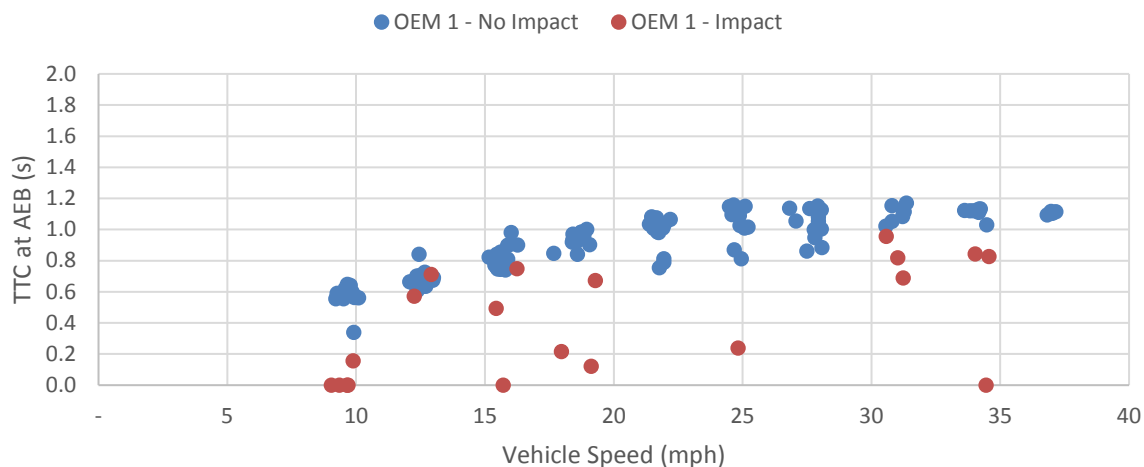


Figure 5. Test Run Results for Production Vehicle 1, Comparing AEB Activation Time to Vehicle Speed in S1-A.

⁴ Overlap refers to point on the front bumper where the pedestrian is projected to impact, given no PCAM intervention.

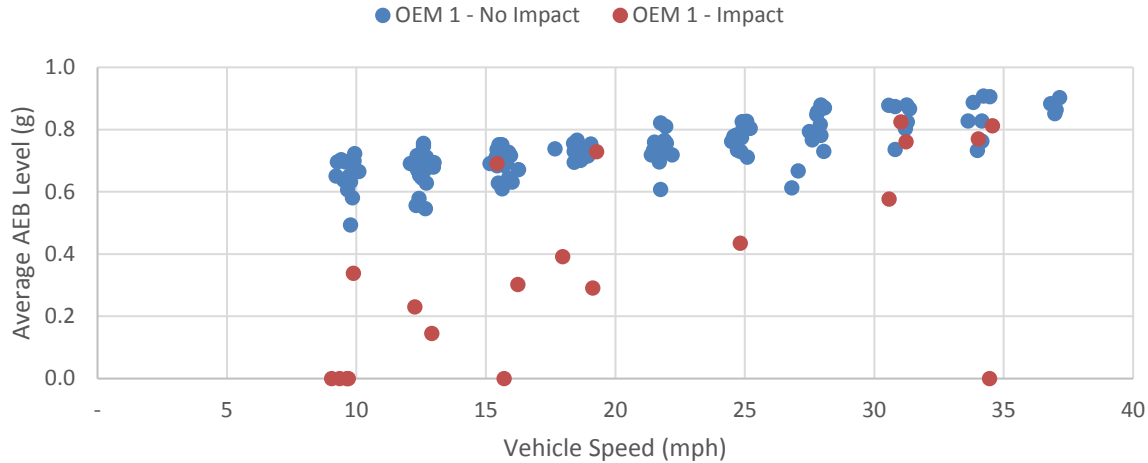


Figure 6. Test Run Results for Production Vehicle 1, Comparing Average AEB Level to Vehicle Speed in S1-A.

Test results show that there is a relationship between AEB activation time and level to vehicle travel speed. This intuitively makes sense, as more time and braking power are needed for the vehicle to come to a complete stop within the finite detection range of the system. Further, it can be seen that although AEB timing and braking varied, there is an overlap in AEB performance and vehicle travel speed and the end result (impact or no impact). In the S1 test setup, the various combinations of conditions allow for the vehicle to stop after the pedestrian's travel path and still avoid the impact (i.e., vehicle slowed enough to allow pedestrian to finish crossing). Even if an impact occurred (potentially due to insufficient AEB) vehicle speed reductions were observed, resulting in lower impact speeds with the pedestrian. Finally, as shown in the figures, in some instances the PCAM system did fail to activate, resulting in an impact at full speed. The test data provided empirical data that were used to estimate system effectiveness.

Human Behavior

Information on driver behavior was obtained from previous research studies, determining driver responses in conflicts with the presence of a warning. Driver performance is incorporated into the treatment data to determine incremental benefits when a warning is issued, along with AEB. As seen in Table 5, based on earlier studies, driver reaction time was estimated as a lognormal distribution with a mean of 1.1 seconds and standard deviation of 0.3 [16]. Also in Table 5, driver braking level was estimated as a normal distribution curve with a mean of 0.5 g and a standard deviation of 0.1 [17]. Only treatment data are necessary, as the benefits method uses a crash reconstruction method. This assumes that all baseline conflicts resulted in a crash regardless of driver response. These parameters are incorporated into the Monte Carlo simulation independently.

Table 5.
Driver Performance Measures in Response to a Warning

Inputs:	Min	Max	Mean*	Std. Dev.*	Distribution Type
Host Driver Reaction Time In Control (s)	0	5	1.1	0.3	Log Normal
Host Driver Deceleration In Control (g)	0.25	0.75	0.5	0.1	Normal

*Mean and standard deviation are based on sample data not population

RESULTS

Results from the benefits model provided information on a PCAM's potential ability to avoid pedestrian crashes and mitigate pedestrian injury through impact speed reduction in unavoidable crashes. The results were derived from crash probability in Equation (3) and the resulting impact speed to determine pedestrian injury in Equation (5). The parameters in these equations were obtained from a crash reconstruction simulation, superimposing empirical PCAM system performance data onto historical vehicle-pedestrian crash cases.

Simulation

A Monte Carlo simulation model exercises general kinematic equations in conjunction with driver and system performance data to determine the probability of a crash and the resulting impact speeds given a crash. Kinematic equations were derived from previous research for the four priority pre-crash scenarios [6]. This simulation reconstructed historical 2011 and 2012 PCAM-addressable GES and FARS crashes and superimposed PCAM system test data and driver performance distribution data to determine the outcome with PCAM intervention.

Initial conditions for the simulation are described by vehicle location, size and speed, pedestrian location, size, and speed, and environmental conditions (e.g., lighting and obstructions). Driver and system performance data are described by driver reaction time, driver braking level, system activation time, and system braking level. The simulation was run for 100,000 iterations.⁵ Each iteration cycles through historical crashes and superimposes PCAM system performance data directly from the test data. PCAM system performance data were tied to historical crashes by correlating the initial conditions (e.g., vehicle speed, pedestrian speed). For example, a crash reporting vehicle travel speeds of 25 mph with a pedestrian walking across the road in the daylight with no obstruction was superimposed with S1-A test data (vehicle speeds of 25 mph), as this scenario is representative of this crash case.

System Effectiveness

System effectiveness is estimated as a range of values, in terms of crash avoidance and injury mitigation, for the three systems types defined earlier, three production vehicles, and six testing scenarios. A refined target crash population is presented in Table 6 representing the historical crashes that may be addressed by PCAM systems in the six distinct testing scenarios, as effectiveness cannot be accurately assessed for other conditions. Costs are calculated from NHTSA economic analyses and are based on 2010 economic costs [14].

Table 6.
Annual Average Number (2011 to 2012) of Target Crashes, Injuries, and Costs (2010\$).

Scenario Name	GES Crashes	FARS Crashes	Costs (2010 \$M)	MAIS 2+		MAIS 3+	
				Pedestrians Injured	Costs (2010 \$M)	Pedestrians Injured	Costs (2010 \$M)
S1-A	4,582	838	\$ 8,393	1,576	\$ 8,269	1,111	\$ 8,083
S1-B	-	1	\$ 5	1	\$ 5	1	\$ 5
S1-C	796	35	\$ 433	150	\$ 408	72	\$ 377
S1-D	279	9	\$ 124	52	\$ 115	24	\$ 104
% PCAM-Addressable S1	76%	63%	64%	66%	63%	64%	63%
S4-A	300	100	\$ 967	160	\$ 959	125	\$ 945
S4-B	471	72	\$ 763	187	\$ 750	120	\$ 723
% PCAM-Addressable S4	26%	28%	28%	29%	28%	28%	28%

From these target crashes, a subset of crashes are identified with enough data to allow for a suitable crash reconstruction. The main factors in eliminating crashes included missing information about vehicle travel speed and pedestrian motion and speed. These specific crashes were then used to determine a baseline harm curve, as described earlier (National Crash Data), for use in Equation (5).

Crash Avoidance The results for crash avoidance system effectiveness are presented in Table 7, based on 100,000 iterations within the Monte Carlo simulation. Results are presented for the various production vehicles using the AEB system logic (i.e., only AEB activates without any driver warning). It is important to note that this system logic is presented because it was determined from the test data that the difference between driver warning and AEB activation was minimal (average less than 1 second) and a driver would not be able to react to the warning prior to the AEB activation. Simulation results confirmed this, as there was minimal crash avoidance effectiveness differences between the three system logic variations.

⁵ A sensitivity analysis was performed to determine the number of iterations for the simulation to enter a stable state. After 2,500 iterations, this analysis entered a steady state within a ± 0.2 percent range.

Table 7.
Crash Avoidance Effectiveness of PCAM Systems for Three Production Vehicles (AEB Only) and Two Crash Databases.

Scenario Name	GES			FARS		
	OEM 1	OEM 2	OEM 3	OEM 1	OEM 2	OEM 3
S1-A	76%	75%	40%	52%	49%	7%
S1-B	N/A*	N/A*	N/A*	10%	68%	0%
S1-C	90%	70%	64%	37%	36%	12%
S1-D	20%	22%	39%	0%	0%	9%
S4-A	49%	64%	53%	39%	51%	34%
S4-B	70%	100%	95%	22%	59%	46%

*No GES crashes met conditions to be reconstructed

Based on the initial conditions and system performance data, the various production vehicles were successful in avoiding many crashes, although they demonstrate lower performance with faster pedestrian speeds and obstructions. Further, results prove that not all crashes are avoidable but a reduction in impact speeds may provide an additional safety benefit.

Crash Mitigation An output of the Monte Carlo simulation is to report the impact speed of the resulting vehicle-pedestrian crash. A distribution of these impact speeds is compared to the baseline impact speeds to determine the potential for reduced pedestrian harm. Figure 7 illustrates an output of the simulation, showing the various distributions of impact speeds for a production vehicle in the S1-A testing scenario within the GES crash reconstructions. Distributions of impact speeds were smoothed using regression modelling to account for data anomalies.

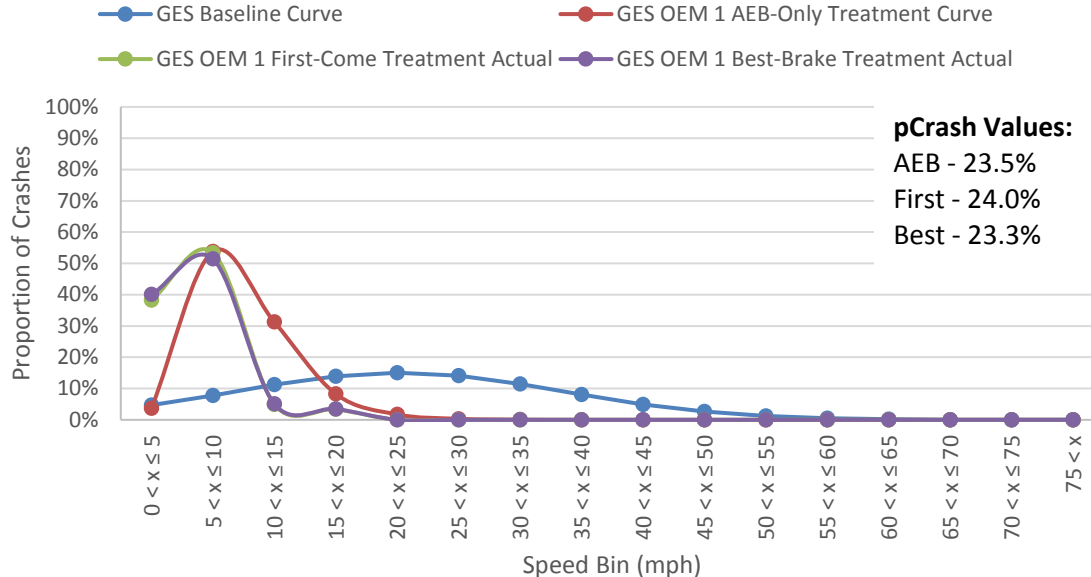


Figure 7. Plots of Functions Comparing Baseline and Treatment Impact Speeds for Production Vehicle 1 in a S1-A Test with GES Crashes.

Results show a distinct shift in the average impact speed, reducing speed from 20-25 mph to 5-10 mph. An impact speed reduction of 15 mph can have a profound effect on mitigating injuries, dropping potential pedestrian injuries from severe to minor. Further, as shown in Figure 7, crash mitigation effectiveness accounts for the crashes avoided, including the 24 percent of crashes avoided, effectively eliminating all subsequent pedestrian injuries (Equation (4)).

Crash mitigation effectiveness for the three production vehicles using the AEB system logic (i.e., only AEB activates without any driver warning) is shown in Table 8. Similar to crash avoidance, the minimal difference in AEB activation and driver warning provided small variations in effectiveness.

Table 8.
Crash Mitigation Effectiveness of PCAM Systems for Three Production Vehicles (AEB Only) and Two Crash Databases.

PCAM Scenario	Harm Measure	GES			FARS		
		OEM 1	OEM 2	OEM 3	OEM 1	OEM 2	OEM 3
S1-A	MAIS 2+	92%	91%	72%	91%	88%	67%
	MAIS 3+	96%	96%	83%	96%	94%	79%
S1-B	MAIS 2+	N/A*	N/A*	N/A*	65%	88%	46%
	MAIS 3+	N/A*	N/A*	N/A*	77%	92%	54%
S1-C	MAIS 2+	89%	79%	46%	83%	79%	64%
	MAIS 3+	90%	83%	38%	91%	87%	76%
S1-D	MAIS 2+	54%	65%	73%	41%	68%	73%
	MAIS 3+	65%	77%	82%	52%	84%	87%
S4-A	MAIS 2+	84%	88%	87%	83%	86%	80%
	MAIS 3+	89%	92%	93%	89%	91%	87%
S4-B	MAIS 2+	92%	100%	98%	78%	89%	85%
	MAIS 3+	96%	100%	99%	86%	93%	91%

* No GES crashes met conditions to be reconstructed

Safety Benefits

PCAM systems can potentially provide a wide range of safety benefits, depending on the initial conditions and the system algorithms. Table 9 presents the crash avoidance effectiveness for the six scenarios tested. The range is defined by the three production vehicles and the two sets of crash reconstruction databases; however as noted earlier, only AEB is used for this effectiveness (i.e., no driver warning). The resulting benefits are determined from Equation (1) using the values from Table 6 and Table 7. These crashes translate to savings in billions of dollars and hundreds of equivalent lives saved (i.e., a metric that translates comprehensive costs into a reduction in pedestrian fatalities).

Table 9.
Annual PCAM-Addressable Crash Mitigation Safety Benefits (AEB Only).

PCAM Scenario	Crash Avoidance Effectiveness	GES Crashes Reduced	FARS Crashes Reduced	Costs Reduced (2010 \$M)	Equivalent Lives Saved
S1-A	7% - 76%	318 - 3,503	58 - 641	\$ 582 - 6,417	64 - 702
S1-B	0% - 68%	N/A*	N/A*	\$ 3*	N/A*
S1-C	12% - 90%	93 - 713	4 - 31	\$ 51 - 388	6 - 42
S1-D	0% - 39%	0 - 108	0 - 3	\$ 48	5
Total Effectiveness of PCAM Addressable S1	7% - 77%	411 - 4,324	62 - 675	\$ 633 - 6,856	69 - 750
S4-A	34% - 64%	103 - 192	34 - 64	\$ 332 - 618	36 - 68
S4-B	22% - 100%	105 - 471	16 - 72	\$ 170 - 763	19 - 83
Total Effectiveness of PCAM Addressable S4	27% - 86%	208 - 663	50 - 135	\$ 501 - 1,380	55 - 151

*Only 1 FARS case was identified over two years, this benefit is simply the effectiveness multiplied by the average annual comprehensive cost (one half comprehensive cost of one fatality).

Table 10 presents the injury mitigation effectiveness for the six scenarios tested. Similar to crash avoidance effectiveness estimates, the wide range of crash mitigation effectiveness is obtained from the three production vehicles and two crash reconstruction databases. Further, crash mitigation effectiveness estimates incorporate the crash mitigation effectiveness. Again, results are only provided for AEB only. Metrics used to estimate injury mitigation benefit are annual reduction of pedestrians injured at MAIS 2⁺, MAIS 3⁺, comprehensive costs, and the number of equivalent lives saved.

Table 10.
Annual PCAM-Addressable Crash Mitigation Safety Benefits (AEB Only).

PCAM Scenario	Harm Measure	Crash Mitigation Effectiveness	Injuries Reduced	Costs Reduced (2010 \$M)	Equivalent Lives Saved
S1-A	MAIS 2+	67% - 92%	1,051 - 1,448	\$ 5,514 - 7,594	603 - 830
	MAIS 3+	79% - 96%	873 - 1,068	\$ 6,347 - 7,767	694 - 849
S1-B	MAIS 2+	46% - 88%	N/A*	\$ 2 - 4*	N/A*
	MAIS 3+	54% - 92%	N/A*	\$ 2 - 4*	N/A*
S1-C	MAIS 2+	46% - 89%	69 - 133	\$ 188 - 364	21 - 40
	MAIS 3+	38% - 91%	27 - 65	\$ 143 - 344	16 - 38
S1-D	MAIS 2+	41% - 73%	21 - 38	\$ 47 - 84	5 - 9
	MAIS 3+	52% - 87%	12 - 21	\$ 54 - 91	6 - 10
Total Effectiveness of PCAM Addressable Total S1	MAIS 2+	64% - 91%	1,142 - 1,620	\$ 5,751 - 8,046	629 - 880
	MAIS 3+	76% - 96%	912 - 1,154	\$ 6,547 - 8,206	716 - 897
S4-A	MAIS 2+	80% - 88%	128 - 141	\$ 764 - 844	84 - 92
	MAIS 3+	87% - 93%	109 - 116	\$ 822 - 881	90 - 96
S4-B	MAIS 2+	78% - 100%	145 - 187	\$ 581 - 750	64 - 82
	MAIS 3+	86% - 100%	103 - 120	\$ 621 - 723	68 - 79
Total Effectiveness of PCAM Addressable Total S4	MAIS 2+	79% - 94%	273 - 329	\$ 1,346 - 1,594	147 - 174
	MAIS 3+	86% - 97%	212 - 236	\$ 1,443 - 1,604	158 - 175

*Only 1 FARS case was identified over two years, this is benefit is simply the effectiveness multiplied by the average annual comprehensive cost (one half comprehensive cost of one fatality).

Overall PCAM systems could provide a crash avoidance effectiveness of 78 percent, as shown in Table 11. Further, the table shows if a crash occurs, PCAM systems may provide injury mitigation effectiveness of 92 and 96 percent for pedestrians injured at MAIS 2⁺ and MAIS 3⁺, respectively. The table only shows the highest crash avoidance and crash mitigation effectiveness observed from the simulation and the correlating benefit.

Table 11.
Best Observed Effectiveness and Safety Benefits for PCAM-Addressable Crashes.

Scenario	Crash Avoidance Effectiveness	GES Crashes Reduced	FARS Crashes Reduced	Costs Reduced (2010 \$M)	Equivalent Lives Saved
S1	76.4%	4,324	675	\$ 6,857	750
S4	85.9%	663	135	\$ 1,380	151
Total System	77.6%	4,987	810	\$ 8,237	901

Scenario	Harm Measure	Crash Mitigation Effectiveness	Pedestrian Injuries Reduced	Costs Reduced (2010 \$M)	Equivalent Lives Saved
S1	MAIS 2+	91.0%	1,620	\$ 8,046	880
	MAIS 3+	95.6%	1,154	\$ 8,206	897
S4	MAIS 2+	94.5%	329	\$ 1,594	174
	MAIS 3+	96.5%	236	\$ 1,604	175
Total System	MAIS 2+	91.6%	1,948	\$ 9,640	1,054
	MAIS 3+	95.8%	1,391	\$ 9,810	1,073

CONCLUSION

This paper developed and applied a methodology to estimate potential safety benefits for existing and near-term production PCAM systems. These systems are vehicle-based pedestrian detection systems that can warn drivers and/or automatically apply the vehicle brakes to avoid a collision or reduce the impact speed. This paper addressed current and near-term production PCAM systems with driver warning and AEB. Safety benefits were estimated in terms of reductions in the number of all annual vehicle-pedestrian crashes, annual vehicle-pedestrian fatal crashes, and annual injured pedestrians at MAIS 2⁺ and MAIS 3⁺ levels, annual comprehensive costs, and annual equivalent lives.

Data sources available at the time of this analysis included national crash databases, test track data, and human behavior information. Additional data were collected using a NHTSA SCI team to detail the dynamics of historical pedestrian crashes, specifically the amount of time the pedestrian was visible to the driver. A crash reconstruction simulation superimposed with empirical PCAM system data was conducted to determine crash avoidance effectiveness and any reduction in impact speed if a crash occurred.

Overall, the methodology presented in this paper relied on the availability and accuracy of real-world data. Ideally, safety benefits would be estimated from empirical crash data over the course of multiple years, comparing crash statistics of vehicle-pedestrian crashes without a PCAM system to crashes with a PCAM system. However, with the current state of crash data and collection methods, information is unavailable to estimate PCAM safety benefits in this method. Future considerations may be made to amend the data collection method to address any deficiencies in the crash data. Therefore, this methodology supplemented historical crash data with objective testing of production vehicle systems and previous literature/research. This information was input into a Monte Carlo simulation to compare historical vehicle-pedestrian crashes with synthetic crashes, superimposing PCAM system performance on these historical crashes. Using this method and the limited data available, safety benefits estimates are presented at a high level.

For this study, objective testing was limited to only three production vehicle systems under six specific conditions. The performance of these three systems was not indicative of system performance for other vehicle systems using other technology. Furthermore, as the technology within PCAM systems continues to improve over time, these three systems may not be representative of all current or future technology. Moreover, the limited objective testing conditions may not take advantage of the full operational capabilities of these PCAM systems. Due to the unknown performance of PCAM systems in other scenarios (i.e., S2 and S3) and other conditions (e.g., adverse weather or minimal lighting conditions), it could not be assumed that PCAM systems will have a positive (or negative) safety

benefit. Not being able to correlate testing conditions to historical crashes required this analysis to take a conservative approach and assume that a significant amount of crashes may not be addressed by a PCAM system (e.g., no safety benefit for crashes in the dark). Additionally, limited information on driver-vehicle interaction of these PCAM systems required this analysis to generalize the interaction with three simplified system logic approaches.

This paper summarizes a multi-year effort of data collection and analysis, as such this paper only describes the methodology and presents a portion of the entire data analysis [18]. The full report with data and analysis can be found at: <https://www.nhtsa.gov/document/estimation-potential-safety-benefits-pedestrian-crash-avoidance-mitigation-systems>

REFERENCES

- [1] National Center for Statistics and Analysis. (2018, March). Traffic Safety Facts: Pedestrians (Report No. DOT HS 812 493). Washington, DC: National Highway Traffic Safety Administration.
- [2] National Center for Statistics and Analysis. (2018, September). Traffic Safety Facts: Summary of Motor Vehicle Crashes (Report No. DOT HS 812 580). Washington, DC: National Highway Traffic Safety Administration.
- [3] Yanagisawa, M., Swanson, E., & Najm, W. G. (2014, April). Target Crashes and Safety Benefits Estimation Methodology for Pedestrian Crash Avoidance/Mitigation Systems (Report No. DOT HS 811 998). Washington, DC: National Highway Traffic Safety Administration.
- [4] National Center for Statistics and Analysis. (2014, December). National Automotive Sampling System (NASS) General Estimates System (GES) Analytical User's Manual 1988-2013 (Report No. DOT HS 812 091). Washington, DC: National Highway Traffic Safety Administration.
- [5] National Center for Statistics and Analysis. (2015, April). Fatality Analysis Reporting System (FARS) Analytical User's Manual 1975-2013 (Report No. DOT HS 812 092). Washington, DC: National Highway Traffic Safety Administration.
- [6] Swanson, E., Yanagisawa, M., Najm, W. G., Foderaro, F. & Azeredo, P. (2016, August). Crash Avoidance Needs and Countermeasure Profiles for Safety Applications Based on Light Vehicle-to-Pedestrian Communications (Report No. DOT HS 812 312). Washington, DC: National Highway Traffic Safety Administration.
- [7] Rosén, E., Källhammer, J.-E., Eriksson, D., Nentwich, M., Fredriksson, R., & Smith, K. (2010). Pedestrian Injury Mitigation by Autonomous Braking. *Accident Analysis and Prevention*, 42, 1949–1957.
- [8] Fredriksson, R. (2015, January). Potential Head Injury Reducing Benefit of Combining Passive and Active Pedestrian Protection Systems [presentation]. 2015 SAE Government-Industry Meeting. Washington, DC.
- [9] Shibata, E. (2015, January). Next Generation EyeSight® and Future Strategy [presentation]. Subaru. 2015 SAE Government-Industry Meeting. Washington, DC.
- [10] Sherony, R. (2015, January). Pedestrian Pre-Collision System (PCS) Test Mannequin and Test Method Development [presentation]. Toyota. 2015 SAE Government-Industry Meeting. Washington, DC.
- [11] Harding, J., Powell, G., Yoon, R., Fikentscher, J., Doyle, C., Sade, D., Lukuc, M., Simons, J., & Wang, J. (2014, August). Vehicle-to-Vehicle (V2V) Communications: Readiness of V2V Technology for Application (DOT HS 812 014). Washington, DC: U.S. Department of Transportation, National Highway Traffic Safety Administration.
- [12] Najm, W.G., and daSilva, M.P. (2000, May). Benefits Estimation Methodology for Intelligent Vehicle Safety Systems Based on Encounters with Critical Driving Conflicts. ITS America 10th Annual Meeting and Exposition. Boston, MA.
- [13] McMillan, N.J., Christiaen, A.-C., & Stark, G.V. (2001, November). Estimating Safety Benefits for the IVI Generation 0 Field Operational Tests. Paper No. 01TB-59. 2001 SAE International Truck & Bus Meeting & Exposition. Chicago, IL.
- [14] Blincoe, L., Miller, T.R., Zaloshnja, E., & Lawrence, B.A. (2015, May). The Economic and Societal Impact of Motor Vehicle Crashes, 2010 (Revised) (DOT HS 812 013). Washington, DC: U.S. Department of Transportation, National Highway Traffic Safety Administration.
- [15] Albrecht, H. (2017, January). Objective Test Procedures for Pedestrian Automatic Emergency Braking Systems [presentation]. 2017 SAE Government-Industry Meeting. Washington, DC.

- [16] Olson, P.L., Cleveland, D.E., Fancher, P.S., Kostyniuk, L.P., & Schneider, L.W. (1984, June). Parameters Affecting Stopping Sight Distance. NCHRP Report No. 270. Washington, DC: Transportation Research Board (TRB).
- [17] Kiefer, R.J., Cassar, M.T., Flannagan, C.A., Jerome, C.J., & Palmer, M.D. (2005, August). Surprise Braking Trials, Time-to-Collision Judgments, and "First Look" Maneuvers Under Realistic Rear-End Crash Scenarios (DOT HS 809 902). Washington, DC: U.S. Department of Transportation, National Highway Traffic Safety Administration.
- [18] Yanagisawa, M., Swanson, E., Azeredo, P., and Najm, W.G. (2017, April). Estimation of Potential Safety Benefits for Pedestrian Crash Avoidance/Mitigation System (Report No. DOT HS 812 400). Washington, DC: National Highway Traffic Safety Administration

ACRONYMS

AEB	automatic emergency braking
CP	crash probability
EM	exposure measure
FARS	Fatality Analysis Reporting System
FOV	field of view
GES	General Estimates System
GIDAS	German In-Depth-Accident-Study
ITARDA	Institute for Traffic Accident Research and Data Analysis
MAIS	maximum abbreviated injury scale
NASS	National Automotive Sampling System
NHTSA	National Highway Traffic Safety Administration
OEM	original equipment manufacturer
PCAM	pedestrian crash avoidance/mitigation
PR	police-reported
SCI	Special Crash Investigation
TRC	Transportation Research Center
TTC	time-to-collision
V2V	vehicle-to-vehicle
VRTC	Vehicle Research and Test Center

APPENDIX

Figure 8. Detailed List of Variables Obtained from NHTSA'S SCI Team for 43 Vehicle-Pedestrian Crashes

Variable	Description
Year	Year of the crash
State	U.S. state of the crash
# Ped. Involved	Number of pedestrians hit by the vehicle
Ped. Age Group(s)	Age of the first pedestrian hit (years) – if multiple pedestrians, another field
Ped. Injuries	Pedestrian injury level on KABCO scale
Weather	Current weather at the time of the crash
Lighting	Lighting at time of crash (e.g., daylight, dark, dark w/ lighting)
Road Surface Condition	Coefficient of friction on road at the time of crash
Speed Limit	Posted speed limit on the road of the crash (km/h)
Intersection?	Did the crash occur at an intersection? (Y/N)
Roadway Alignment	Road alignment (e.g., straight, curve)
Roadway Grade	Roadway grade
Traffic Control	Traffic control at the crash location (e.g., lights, stop sign, none)
Veh. Pre-Crash Man.	Vehicle maneuver in the pre-crash scenario
Veh. Avoidance Man.	Vehicle attempted avoidance maneuver (e.g., brake, steer, brake and steer)
Travel Lane #	The vehicle travel lane (numbered left to right of driver)
Veh. Speed	Vehicle pre-crash speed (km/h)
Veh. Speed Range	Potential error range on the pre-crash vehicle speed (km/h)
Distance from Ped.	Vehicle distance from pedestrian when the pedestrian entered the road (m)
Veh. Dist. Range	Potential error range on vehicle distance from pedestrian (m)
Driver Vision Obstructed?	Was the driver's vision obstructed?
Vision Obstruction	What obstructed the driver's vision?
Driver Eyes Off Road?	Were the driver's eyes off the road?
What Driver Looked At	What was the driver looking at if the eyes were off the road?
Ped. Man. Pre-Crash	Pedestrian's pre-crash maneuver (e.g., crossing road, walking, jogging, standing)
Ped. Avoidance Man.	Pedestrian avoidance maneuver (e.g., walk, run, yell, none)
Ped. Location Pre-Crash	Pedestrian's pre-crash location
Ped. Speed	Pedestrian's movement speed (km/h)
Ped. Direction	Direction of pedestrian movement (left-right or right-left of vehicle)
Ped. Vision Obscured?	Was the pedestrian's vision obscured?
Ped. Vision Obscured by?	What obscured the pedestrian's vision?
Ped. Impaired?	Was the pedestrian impaired? (include description of impairment)
Ped. Inattention?	Was the pedestrian inattentive?
Ped. Inattentive Because?	Why was the pedestrian inattentive?
Distance Away from Roadway OR Line of Sight of Car	Vehicle distance from pedestrian when the pedestrian entered the road or was first visible (m)
Location of impact	Where the impact happened (e.g., roadway, crosswalk)
Travel Lane Location of Impact	The lane of impact (numbered from left to right of vehicle)
Distance From Curb	How far from the curb the impact happened (m)
Before, Middle, After Int.?	Did the impact occur before, inside of, or after the intersection?
Area of Impact on Veh	Part of the vehicle that made contact with pedestrian
Distance Traveled by Veh.	Vehicle distance from pedestrian when the pedestrian entered the road (m)
Time Ped. Spends in Roadway	Time the pedestrian spent in the roadway visible and in path of vehicle (s)
Related Factors/Causal Factors	Any related factors that may have contributed to the crash?
PCAM Warning Helpful?	Would a PCAM warning have been helpful for this crash?
PCAM Automatic Braking Helpful?	Would AEB have been helpful for this crash?
PCAM Automatic Steer Helpful?	Would automatic steering have been helpful for this crash?
Summary	Written description of the entire crash scenario
Scene Diagram and photos	Diagram of crash scene and picture of vehicle (contact area, damage) and scene (location)
GPS Coord.	GPS coordinates of the scene of the crash
Impact Speed	Vehicle impact speed (km/h)
Final Rest v1 and p1	How far the vehicle and pedestrian moved after impact until it came to a stop (m)

INFORMED TRUST – AN EXTERNAL USER INTERFACE FOR HIGHLY AUTOMATED VEHICLES

Alexander Mankowsky

Stephan Mücke

Daimler AG

Germany

Paper Number 19-000304

ABSTRACT

Traffic research so far was focused on accidents and accident prevention. With the introduction of automated or semi-automated cars into the public realm however, the question is, how automated cars must be designed to blend in.

The presentation is based on the approach of traffic seen as a cooperative activity, where people are implicitly collaborating in the frame of given traffic rules. The Perception Action Model (PAM, Stephanie Preston 2007) in short suggests that perception and action are inseparable - people perceive actions of others and act immediately. This process is mutual and draws on empathy to predict the activities of the others. “Mind-Reading” (Eric Kandel, 2012) enables to read mood, energy, intention out of the other traffic participants.

Today it seems sufficient to perceive the way other drivers move their vehicle to trigger the Mind Reading process and enable predictive behavior. In case of automated vehicles, human perception has to be triggered properly to avoid misinterpretation or just wrong results of the empathic process.

Based on this approach the presentation introduces an experimental external user interface for highly or fully automated vehicles to address the underlying functionality of traffic. It includes the following features

- Indication of highly automated mode according to and exceeding the SAE recommendation
- Signaling of cooperative behavior
- Communication especially with vulnerable road users.

The system is demonstrated in various everyday driving situations on highways and city roads, such as merging traffic or a stop for pedestrians at a cross walk. Especially the aspects of an intuitive and intercultural understanding are discussed.

In addition, the external user interface can be used to share the vehicle’s knowledge about impending dangerous situations with its immediate surroundings – thus helping others to avoid potential accidents.

The presentation aims to demonstrate and discuss how an intuitively designed external user interface can help build informed trust in highly automated vehicles as a major factor of success and even give back to society by sharing its situation awareness.

Informed Trust is a major factor of success for Real-Word Deployment of Automated Driving Systems.

Most of the time our movement through the public realm is simply uneventful, and it is so because humans are cooperating with one another to make it so [1].

Traffic research has so far focused on accidents and accident prevention. With the introduction of automated or semi-automated cars into the public realm, however, the focus changes to understanding the magic of normal traffic and asking the following questions: how do we manage to avoid bumping into each other all the time? What will happen when automated cars are mixed into the magic? Automated cars must be designed to blend into this process; otherwise, known types of accidents will only be replaced by new types of accidents.

We have developed a conceptual framework, building on Social Sciences and Neuroscience, to understand the behavior of the involved actors in mobility. *Informed Trust* is our approach to designing self-driving cars in such a way that allows all actors to achieve agency. The overarching goal is to enable all actors in mobility to *produce a successful and harmonious mobility*, with fewer accidents than in today's traffic.

CONCEPTUAL FRAMEWORK

What is Mobility?

We are walking in crowded places, driving in crowded streets, and usually nothing bad happens – we manage. For the eye, it is mostly just a flow of people, cars, cycles and other means of mobility. *“The sociologist Lyn Lofland argues persuasively that the ordinary flow of movement on big - city sidewalks should be regarded as a collaborative production — a hard - won achievement in “cooperative motility” that requires the most sensitive attention to the subtle signals other pedestrians issue as to their intended course and speed.”* Lyn Lofland and others [2] are comparing our movement with a dance: we assume the movements of the others, as they do our own, and adapt continuously. As a result of the cooperative mass behavior, a rhythm emerges. Many cities are producing their own rhythm on a daily basis – you have to adapt, when switching from slow motion Charlotte, North Carolina to busy and dense NYC. For our topic, it is important to notice that walking, driving, riding a bike or a scooter is, from the standpoint of cooperation, the same. Somehow, we manage to predict the behavior of the others and adapt immediately. With self-driving cars, we introduce robots into the collective dance. Since we have not yet experienced robotic behavior in the public realm, the smooth collective dance may not happen. Practically speaking, will their behavior provoke dangerous situations? What can we do to avoid this?

Mobility is a cooperative activity par excellence

The Role of Empathy in Mobility

Our approach is based on traffic seen as a cooperative activity, where people are implicitly collaborating in the frame of given traffic rules. Normally, we do not have to think while moving. We avoid accidents automatically. It is a subconscious process. One model from Neuroscience to explain our capabilities is the Perception Action Model, from Stephanie Preston and Frans de Waal [3]. In short, it suggests that perception and action are inseparable - people perceive actions of others and act immediately. This process is mutual, and draws on empathy to predict the activities of the others.

The need for empathy as a basic function of life is simple: individually, we have to find out about the intentions of other actors in our environment, and decide to run, approach, or simply freeze¹. Therefore our perception scans our environment for signs of life – most importantly, for eyes watching us.

You can test it for yourself: you will be aware of the first raindrops at the window, but soon they will be not interesting anymore – they do not show signs of intention. They are not *alive*. However, if a fly approaches the same window, your perception will give you notice. Our eyes are moving more than a 100.000 times a day to achieve this, without giving us any awareness that they do so. Our perception-action mechanism runs on its own.

A hypothesis on empathy is that we incorporate the movement of other living beings. While doing so, a feeling emerges in us as we wonder how the other living being might feel and what it is up to. Neuroscientists like Erik

¹ Freezing in the face of danger implies that we are not able to drive accident free without assistance systems

Kandel [4] call this process 'Mind Reading'. It works well with living beings showing a direction when moving, like all mammals do.

Applied to traffic, it enables us to read the mood, energy, and intentions of the other traffic participants.

Today it seems sufficient to perceive the way other drivers move their vehicles to trigger the Mind Reading process and initiate predictive behavior. If empathy is impaired, like in people who suffer from autism, driving can become quite exhausting, which underscores the importance of empathy as a basic functionality for fluid cooperation in traffic.

With self-driving cars however, empathy will fail, unless measures are taken design wise.

Non-deterministic automation in Self-Driving Cars

Self-driving cars are complicated constructs based on Machine Learning (ML) for the interpretation of the traffic scene. ML is basically a statistical process. Training data are fed into the system, until the systems can label their environment sufficiently. Since the training data and the real environment are never the same, the labeling cannot be deterministic and proven 100% right. ML based systems are therefore non-deterministic systems. Possible errors are falling into three categories: mismatch in given categories, like a mismatch between a pedestrian and a cyclist, or a total failure like labeling a golf players portrait as a golf ball, caused by golf balls visibility in too many pictures used for training the ML system. Therefore, the non-deterministic ML systems must always be framed by a classical deterministic system as a backstop. In self-driving cars, for example, a simple radar system, which overrides the ML system and stops the car, when something is sensed on the road that contradicts the traffic scene created by the ML program.

The resulting behavior of a self-driving vehicle can be weird [5] for us, because our prediction skills fail against non-deterministic automation.

To enable our predictive capabilities, the car needs to provide hints for our perception, so that we can 'feel' it the way we can feel other participants in traffic.

Design Approach - Informed Trust

Informed Trust is opposed to blind trust: the goal of *Informed Trust* is to enable all the participants in a traffic scene to act: in short, to foster agency. Without agency, some actors in traffic will end up as victims by design, others as villains, also by design² [6].

To enable agency when dealing with self-driving cars, we have to prepare design elements working as handles for empathy, design elements functioning as enablers for learning, and finally, define procedures for when the systems degrade.

Informed Trust: Empathy and insight

Empathy: Feel the car

- Has it seen me? Is it friendly? Is it coming?
- Which direction is it heading? Is it relaxed or strained?
- Shall I help? Is it helping? I miss it already!
- Is it aware of me?

Insight: Learning process

- Display the mode of the car: is it in self-driving mode or not

² Compare 'Moral Machines' from MIT, Iyad Rahwan, Jean-Francois Bonnefon, Azim Shariff. Once you enter the game-like traffic situation, you end up as a executioner by design. <http://moralmachine.mit.edu/>

- Avoid misinterpretation of the role of a person sitting in the driver's seat
- Predictability of the car in different situations
- Offer simple conceptual models of the technical functions

Lessons: Graceful degradation

- Clear functional steps in case of break down
- Universally understandable warning signs to driver and traffic
- Standard procedure in case of accident detection

Empathy is based on functions of our perception. Our perception is scanning our environment continuously for body-movement and eyes. Once we encounter life, the prediction process starts. For a self-driving car, the communication of intention and state through movement can be implemented in several ways. The body of the car itself can be set in motion, parts of the cars body can be used, the way it is moving ahead, creeping, accelerating, decelerating and so on. The body of the car can be equipped to simulate muscle movement or wrinkles.

We experimented successfully with a wake-up motion of the car similar to an animal³ [7]. The result was awareness on the side of pedestrians in front of the car when it 'awakes' in the parking lot, without any alarmism. The effect triggered a reaction which was felt by test participants as quite natural.

The importance of eye contact is paramount for informed trust. It can be implemented through various means, such as an LED pointing at people within a critical distance. These LEDs can be programmed to follow somebody, communicating to them a 'Hey it's you'. A short blink is similar to what we are doing regularly when walking the street. We also used a virtual shadow on the surface of the concept-car Vision URBANETIC, which is more complicated to implement, but very natural. Once we get used to such a shadow, we get alarmed when it is missing, and are so able to avoid a possible accident. Moreover, directed sounds are helpful to underscore urgency to make contact, especially for the visually impaired.

To ensure the empathic effect, the tools should work together organically. Our perception is watching for signs of life, so we should strive for a 'half-life' approach, as we know it from animated objects.

Insight needs simple and dependable signaling on the side of the self-driving car. In traffic school for children, it should be as easy as possible to teach them how to interact with such a car.

Teaching example for children:

- | | |
|-----------------------------------|----------------------------------|
| 'Is the car in self-driving mode? | - Watch for the signaling lights |
| 'Has it seen you?' | - Check signs of eye contact |
| 'No signs of eye contact?' | - Go away |

To achieve this scenario, the car must show its state as self-driving in 360 degrees around the car. The signaling should be arranged in such a way that the signal is applied in direction of the driver's seat, as it is the ritualized direction of the short gaze. The mode signaling has to be standardized. Standardization here is seen as the single most important success factor for the application of the technology.

Lessons have to be prepared for the case of a system failure. When the system is failing, it has to use a standard procedure, also known as Graceful Degradation in automation. To know this procedure will be most important for

³ Clifford Nass, Psychology of Automated Vehicles, Stanford, 2013.

Nass suggests to compare self-driving cars with domesticated animals and design the interaction-narrative accordingly. <https://www.youtube.com/watch?v=hrxf7lG-j9c>

people inside and outside of the car. Graceful Degradation is fundamental to the debate on ethics and automation. From the perspective of the program running a self-driving car, an accident is always a failure out of missing or incorrect data, with failed prediction as the outcome. The concept of Graceful Degradation can be helpful here, defining the standard procedure in such a case. Straight emergency braking will give the other actors in the accident scene the opportunity to act meaningfully, once they know for sure that all self-driving cars will behave in exactly this way.

INTRODUCING AN EXTERNAL USER INTERFACE FOR AUTOMATED VEHICLES

Sensor setup, high-definition maps and digital integration

The environmental perception system of automated vehicles consists of sensors and perception algorithms. Their customized sensor setup uses various sensor types like radars, lidars, cameras and ultrasonic sensors as well as microphones. It provides a robust 360-degree field-of-view around the vehicle to enable the vehicle to handle all relevant use cases and maneuvers [1].

Deep Learning algorithms allow an object classification. The example in figure 1 illustrates different object classes by color-coding: vehicles are shown in blue, pedestrians in red, the road in purple, and traffic signs in yellow. It even includes objects partially blocked from the automated vehicle's perception system, such as pedestrians partially hidden by other vehicles.



Figure 1. Object classification based on camera images [8]

A high-definition digital map defines the operational design domain and allows locating the automated vehicle and surrounding vehicles, pedestrians and objects. Environment modeling anticipates and predicts what other objects on the roadway might do.

Automated vehicles will be integrated within a digital infrastructure, which is capable of connecting to a Fleet Operations Center, data sources from public agencies (e.g. traffic signal data from local road authorities) and data from other vehicles. It also has an interface to the cloud where information such as status reports, relevant traffic, weather, incident and construction zones can be accessed.

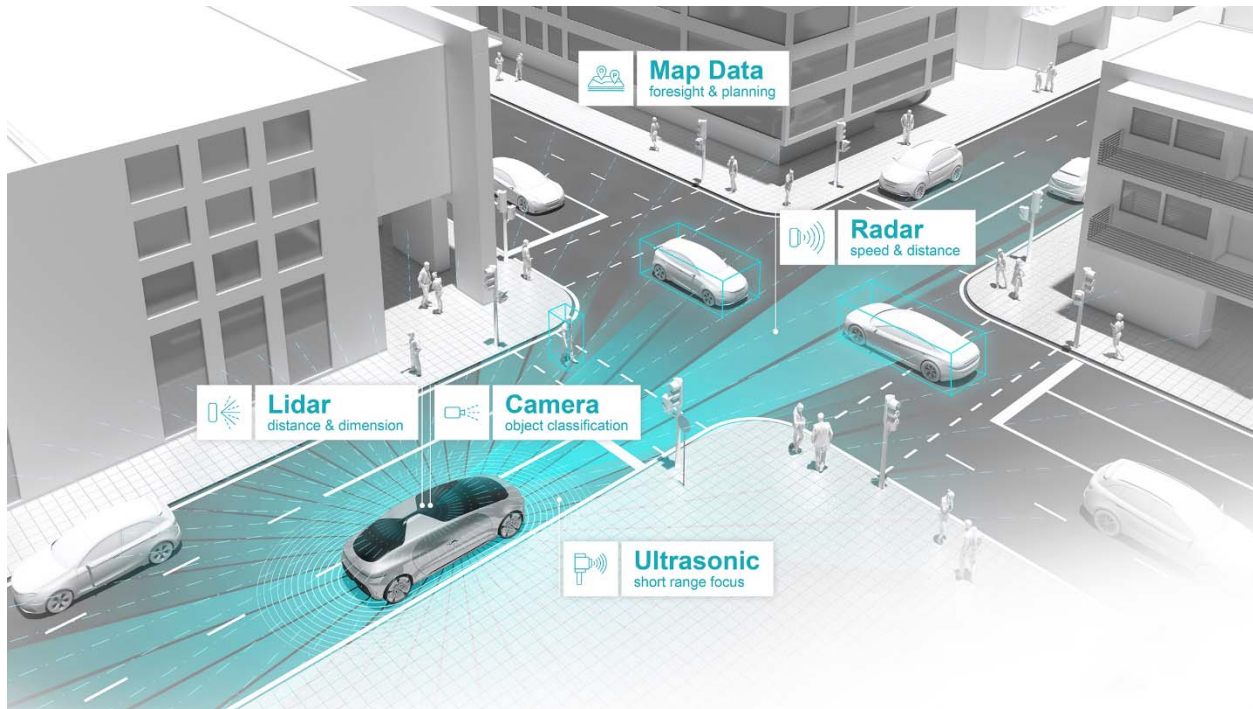


Figure 2. Sensor setup of an automated vehicle

External User Interface

Indication of automated driving mode

As mentioned in the context of interaction with pedestrians, the indication of automated driving mode is essential for the acceptance of automated vehicles. It allows pedestrians and other road users to identify automated vehicles, learn to read their intentions and thus build the aforementioned “informed” trust.

In 2018, Mercedes-Benz and Bosch started an Automated Valet Parking Service as a pilot project in Stuttgart [9]. Figure 4 shows a first realization to indicate the automated driving mode using turquoise illumination of already existing lights in the exterior mirrors and the third brake light.



Figure 3. Automated Valet Parking: Indication of automated driving mode [9]

Turquoise was chosen as indication of automated driving mode because it is unique, even peripherally visible and not used for any other exterior vehicle lighting. An internal Mercedes-Benz study with pedestrians revealed that a majority of the participants preferred turquoise and all of them voted for the 360° indication. Mercedes-Benz is supporting activities of the SAE, to develop an exterior lighting concept for automated vehicles.

Intuitive communication with other road users

In many situations road users, especially pedestrians should know instantaneously and reliably what an automated vehicle will do next.



Figure 4. Communication with a pedestrian wanting to cross the road [10]

Signaling cooperative behavior

An important goal for automated vehicles is to reduce the likelihood of accidents and to mitigate risks for passengers and other road users by operating like a defensive and attentive driver who consistently monitors the driving environment and responds appropriately and safely to changing conditions. However, trust in automated vehicles doesn't only require their cooperative behavior. They also must inform their immediate surroundings about their intentions in a way that can be understood intuitively.

Again, the combination of an indication of autonomous driving mode and an intuitively understandable message help other drivers to learn the behavior of automated vehicles and to build “informed” trust.

Warnings

In addition, the external user interface is used to share the automated vehicle's knowledge about impending dangerous situations with its immediate surroundings – thus helping others to avoid potential accidents.

Especially vulnerable road users like pedestrians and bicyclist who are easily missed or obscured and do not have their own assistance systems may profit from this feature.

Local Hazard warnings: Driving safely and smoothly in complex environments requires detailed and ongoing awareness of the real-time traffic situation, coupled with the ability to forecast future traffic developments.

CONCLUSIONS

The presentation aims to demonstrate and discuss how an intuitively designed external user interface can help to build informed trust in automated vehicles and to create an additional safety benefit for others by sharing its situation awareness. The Mercedes-Benz Experimental Safety Vehicle 2019 (Experimentales Sicherheitsfahrzeug ESF 2019) will show how these considerations can be implemented in future vehicles.

REFERENCES

- [1] Lofland, Lyn H. The Public Realm, p. 29. Taylor and Francis, 1998. Kindle Edition.
- [2] Greenfield, Adam. Radical Technologies: The Design of Everyday Life. Verso, 2017. Kindle Edition, Location 1296
- [3] Preston, Stephanie D. and de Waal, Frans B.M. (2001) Empathy: Its ultimate and proximate bases. https://greatergood.berkeley.edu/images/uploads/Preston_dewaal2002.pdf
- [4] Kandel, Eric: Age of Insight, 2012. The hypothesis may explain why some people are afraid when encountering spiders or snakes. We cannot replay their behavior, and therefore not predict what they are about to do. Could be similar when encountering robots and self-driving cars
- [5] The State of Self-Driving Cars in 2018, <https://www.youtube.com/watch?v=1Jf1ZM-ho4o>
- [6] Rahwan, Iyad; Bonnefon, Jean-Francois and Shariff, Azim: Moral Machines. MIT. <http://moralmachine.mit.edu/>
- [7] Nass, Clifford: Psychology of Automated Vehicles, Stanford, 2013.
- [8] “Reinventing Safety: A Joint Approach to Automated Driving Systems”, Mercedes Benz in cooperation with BOSCH, VSSA, 2018 Mercedes-Benz Research & Development North America, Inc. and Robert Bosch LLC. <https://www.daimler.com/dokumente/innovation/sonstiges/vssa-mercedes-benz-and-bosch.pdf>
- [9] Future insight: <https://media.daimler.com/marsMediaSite/de/instance/ko/Mercedes-Benz-FutureInsight-Human-first-Empathie-als-Anker-in-der-digitalen-Transformation.xhtml?oid=41918249>
- [10] Automated Valet Parking: https://media.daimler.com/marsMediaSite/de/instance/ko.xhtml?oid=23076118&ls=L3NIYXJjaHJlc3VsdC9zZWZyY2hyZXN1bHQeGh0bWw_c2VhcmNoU3RyaW5nPXZhbGV0K3Bhcmtpbmc2VhcmNoSWQ9MCZzZWZyY2hUeXBIPWRldGFpbGVkZmJvcmlcnM9dHJ1ZSZyZXN1bHRJbWZvVHlwZUIkPTQwNjI2JnZpZXdUeXBIPWxpc3Qmc29ydERlZmluaXRpb249UFVCTEITSEVEX0FULTImdGh1bWJTY2FsZUluZGV4PTAmcm93Q291bnRzSW5kZXg9NQ!!&rs=1

POWER REQUIREMENTS FOR A REDUNDANT AUTOMATED STEERING SYSTEM FOR TRUCKS

Herold, Maximilian

Liebler, Maximilian

Winner, Hermann

Institute of Automotive Engineering, Technische Universität Darmstadt, Otto-Berndt-Str. 2, 64287 Darmstadt
Germany

Paper Number 19-0302

ABSTRACT

For automated driven vehicles with a driving automation level above two, the driver is not available immediately as fallback when the automated driving system fails. Therefore, a redundant design for each automated driving system (e.g. the automated steering system) is a central safety requirement. The grade of redundancy, i.e. if it has to be fully fail operational or just a certain level of fail degraded, depends on the definition of the safe state in case of a failure and on the way how to reach it. The safe state itself depends on the driving situation respectively the type of road, where the automated vehicle is driving. The goal of this article is to determine the amount of steering power and energy required in different use cases and road types to reach the safe state.

Therefore, a definition of the safe state for automated driving trucks is determined using the ISO 26262 and existing definitions. With the help of German national road construction guidelines for highways, rural roads and urban roads, the safe state and the necessary driving maneuvers to reach it are determined for different defined road types. A 12-t two-axle truck has been equipped with measurement equipment as test vehicle. The determined driving maneuvers to reach the safe state are driven with the test vehicle and the required steering power and steering energy are measured.

The results of this investigation are the minimum required steering torque, power and energy for each tested driving maneuver. The minimum redundancy requirements to the automated steering system for a specific use case of automated driving, such as fully automated highway driving, are determined considering all driving maneuvers to reach the safe state in the worst case. Depending on the intended use cases for the automated vehicle, different fallback requirements are determined for the redundant automated steering system. Although the achieved results of this contribution are only representative for the used test vehicle, they are still helpful to get an impression and some real data for the required fallback steering torque, power and energy. It has to be considered that the required steering power and steering energy are highly influenced by the front axle load and thus by the load of the vehicle and by the steering and axle geometry of the vehicle as well. However, based on the findings of this article, the fallback concepts of future redundant active steering systems for highly and fully automated driven trucks can be developed according to the intended use cases.

The requirements for the mentioned exemplary use case of fully automated driving on highways with hard shoulders are very low, thus it should be possible to realize the steering redundancy with low effort. However, for other use cases the redundancy requirements are much higher.

INTRODUCTION

Automated driving is a key topic of development not only in the passenger car industry, but also in the commercial vehicle industry. The increase of safety, the reduction of emissions and the cost saving are the main motivation for such development actions. Whereas there are no technical hurdles for partial automated driving of trucks, e.g. Adaptive Cruise Control (ACC) with Lane Keeping Support (LKS), there are still a lot of open questions, before highly automated driving can be introduced on public roads. Exemplary systems with higher levels of automation are “exit-to-exit highway automation”, “traffic jam assist” or “automated trailer backing” [1].

One of those challenges is to ensure a safe operation during highly automated driving in all possible situations, which also includes a malfunction of one of the systems, which are necessary for the automated driving. [2] categorizes the levels of driving automations, whereby partially automated driving is listed as level 2 (AD2) and highly automated driving is listed as level 3 or higher (AD3+). The driver is not available anymore as immediate fallback level for AD3+. Hence, the automated system has to be redundant and has to provide its own fallback level for the case of a malfunction. This redundancy can be realized inside one system or outside by an additional system. In case of an automated steering system, the steering system can be redundant by itself, but a steering function can also be realized by the brake system using differential braking to steer the vehicle. Although it is possible to steer a truck with the brake system, [3] proofs that it is not feasible for all relevant driving maneuvers of a truck. Additionally [4] argues that the dynamic and the precision of brake steering is not sufficient for the use as steering redundancy. Thus, a redundant automated steering system is mandatory for AD3+.

This article covers the question, how much steering torque, steering power and steering energy is required for the fallback level of a redundant automated steering system for trucks. Therefore, the used research methods are described first and the different results of the investigation are shown and explained afterwards. The article ends with the conclusion of the obtained test results and their discussion.

METHODOLOGY

For the determination of the demanded fallback steering requirements, it is necessary to derive the requirements for a safe state of a truck. Different safe states are defined for different Road Classes using these requirements and German guidelines for road construction. With this definitions, it is possible to determine the different relevant maneuvers, which are necessary to reach the defined safe state. With the help of a test vehicle equipped with measurement equipment for steering torque and angle, the steering power and the steering energy required for each relevant driving maneuver are recorded. The steering redundancy requirements are derived from the measured test data and the determined relevant maneuvers to reach the safe state.

Definition of a Safe State

Since an automated driven vehicle contains a lot of E/E systems (electric/electronic), the definition of its safe state bases on the ISO 26262 on functional safety of E/E systems of vehicles. According to [5] the safe state is defined as an “operating mode of (a vehicle) without an unreasonable level of risk”, whereas the risk is defined as the “combination of the probability of occurrence of harm and the severity of that harm” and the harm is the “physical injury or damage to the health of persons”. In the context of automated driving [6] describes the safe state as an operating mode, where no unreasonable risk occurs for all persons involved in road traffic. Thus, the internal system state as well as the environment of the vehicle are important for the safe state.

Based on the definitions from the ISO 26262, eight requirements of the safe state are determined here (See Table 1). The first requirement is the most important and a high-level requirement. All the other requirements serve to fulfill this superior requirement. The requirements no. 2 to no. 6 are the important requirements for this investigation. The safe state in each specific driving situation depends on those five requirements. Therefore, we separate the safe state for city roads, country roads, and highways.

Table 1.
Requirements to the Safe State of an Automated Driven Vehicle

No.	Requirement
1	No hazard for passengers, other road users, pedestrians or for the environment
2	Vehicle stands still
3	Visibility to other road users bigger than required stopping visibility
4	Relative velocity to other road users less than 70 km/h
5	No blocking of rescue routes
6	No blocking of bridges, tunnels, intersections or roundabouts
7	Protection of the stopping place and warning of other road users
8	Emergency call (if necessary)

To define a safe state for each different type of road, it is important to know all the specific properties of each type, especially according to the possibilities for a safe stop of the vehicle. The German guideline for the construction of city roads [7], the guideline for the construction of country roads [8] and the guideline for the construction of highways [9] describes the properties of the roads and are used to define three different Road Classes according to the possibility for a safe stop.

The different types of roads are characterized into three Road Classes (see Table 2). The number of lanes, counting both directions, the availability of a hard shoulder or an emergency stopping bay, the speed limit, the minimum curve radius and the maximum required stopping visibility are used for the classification. The first Road Class contains the roads with a permanent hard shoulder, i.e. highways except urban highways. The second Road Class describes the roads with emergency stopping bays instead of a permanent hard shoulder, i.e. urban highways and big country roads with two lanes at least in one direction. The last Road Class, which requires steering maneuvers to get to a safe state, contains the roads without a hard shoulder and without any emergency stopping bays. City roads are not part of these three classes, because according to [7] there are always speed limits below 70 km/h. A relative velocity to other road users of more than 70 km/h is not possible. Hence, the transition to the safe state is

always an immediate braking maneuver and no steering is required for this classes. The claim is, that the automated vehicle knows what the safe states and the maximum distances between the single safe states are and how it gets there, depending on the Road Class.

Table 2.
Characterization of Road Classes according to [7], [8], [9]

Class	1	2	3
Number of lanes (both directions)	≥ 4	≥ 3	2
Hard shoulder available?	yes	partially	none
Emergency stopping bay available?	-	at least every 1000 m	none
Speed limit	none	≥ 100 km/h	≤ 100 km/h
Minimum curve radius	470 m	280 m	200 m
Maximum required stopping visibility	250 m	190 m	160 m

The safe state of the class with a hard shoulder is the stand still on the hard shoulder. Usually, no other road user drives on the hard shoulder, thus there is no relative velocity to others. In addition, the stopping visibility has no influence on this safe state and no bridge, tunnel or rescue route is blocked here. The relevant maneuvers to reach the safe state depends on the amount of lanes of the road and on which road the vehicle drives currently, when a failure occurs and the transition to the safe state is required. If the vehicle is not on the lane next to the hard shoulder, one or more lane changes and the change to the hard shoulder are the relevant maneuvers to reach the safe state. Because in areas of highway accesses or exits are no hard shoulders, a change to the hard shoulder could be temporarily not possible. In that case, the vehicle needs to drive on for a defined distance until the hard shoulder is available again.

Driving into and stopping inside an emergency stopping bay is the safe state of the second Road Class, where such a stopping bay intended to be every 1000 m. The emergency stopping bays are at least 84 m long and 3 m wide according to [8]. Because the emergency stopping bay is no continuous lane, no other road user is able to drive on it, whereby the risk seems to be lower standing inside an emergency stopping bay as standing on a hard shoulder. The relevant maneuvers to reach the safe state inside a stopping bay contain one or more lane changes as well, the drive and stopping maneuver into the stopping bay and the required drive on to the next available stopping bay. It is also possible, that there are temporarily hard shoulders available on this Road Class, but for the design requirements of the steering system, the highest fallback requirements are used, which occur for the drive into an emergency stopping bay for this Road Class.

Because of the missing hard shoulders and the missing emergency stopping bays, the safe state of the third class is not obvious. A safe stop at the side of the road is usually not possible due to a relative velocity to the other road users above 70 km/h. However, in practice there are frequently junctions appearing on this class of roads, whereby a turn-off to a side road with a speed limit lower than 70 km/h or to a road with a hard shoulder or emergency stopping bays is possible. A safe stop on such a side road, e.g. a city road, represents the safe state in this Road Class. Hence, the relevant maneuvers are the drive on until the next turn-off to a side road and the turn-off maneuver itself. Of course, it is possible, that there is a stopping bay or a parking lot at this Road Class as well, but this is an exception and the fallback requirements of the steering system are higher for the turn-off maneuver thus these are the crucial design requirements.

Driving Maneuvers

Based on the previous defined safe states for the three different Road Classes, the different relevant driving maneuvers (see Table 3) are performed with a 12-t truck meanwhile the required steering torque, steering power and steering energy are recorded.

Besides the previous mentioned relevant driving maneuvers, the avoidance maneuver is also considered as relevant, because it is possible at any time and at any Road Class, that an avoidance maneuver becomes necessary. The different types of maneuvers are driven several times on several roads, i.e. different routes of country roads, different highways and different city routes were tested. For each type of maneuver, the biggest occurring values for torque, power and energy are used to determine the fallback requirements. With this approach, it is supposed to cover the worst case of each type of maneuver. The measured data of the several maneuvers are combined according to the definition of the safe state in the previous chapter to determine the final fallback requirements for each Road Class. Hereby, the most critical moment for the failure of the steering system is assumed. However, a complete cover of all possible situations is not guaranteed of course.

Table 3.
Relevant Driving Maneuvers driven by 12-t Truck

Maneuver type	v_{\max} in $\frac{\text{m}}{\text{s}}$	$a_{y,\max}$ in $\frac{\text{m}}{\text{s}^2}$	R_{\min} in m
Turn-off to side road (out of city)	-	5,00	70
Lane change (slow)	17	1,37	-
Lane change (fast)	25	2,16	-
Avoidance maneuver	17	5,00	-
(Big) Emergency stopping bay [8]	25	1,96	-
(Small) Emergency stopping bay [8]	17	1,57	-
Highway access/exit	-	3,14	150
Highway interchange	25	3,14	400
Road Class 1	25	2,45	470
Road Class 2	25	3,43	280
Road Class 3	20	3,43	140
Mountain pass	17	3,53	45
City driving	14	3,24	50

Test Equipment

For the test drives, a fully loaded 12-t truck is used with a measured front axle load of 42.6 kN (vehicle data see Table 6 in Appendix). A measurement steering wheel records the torque and the steering angle at the steering wheel. Strain gauges are applied at the pitman arm to measure the output steering torque of the steering system. In addition, the acceleration in all three directions, the velocity and the GPS position of the truck are recorded as well.

The steering angle velocity of the pitman arm is derived from the measured steering wheel angle and the known ratio of the steering gear. The measured output steering torque is integrated over the steering angle at the pitman arm and thus determines the overall steering energy, which itself determines the steering power by derivation over time. Exemplary for the data recording, the measured steering torque at the pitman arm, the measured angular velocity at the pitman arm, the calculated steering energy and power as well as the particular maximum values are shown in Figure 3 (see Appendix) for the maneuver highway exit.

Requirements for a Redundant Automated Steering System

The feature of a redundant automated steering system is the fail operational fallback level integrated inside the steering system. Hence, in case of a partial failure of the steering system, it is still able to steer the vehicle safely without the need of a take-over by the driver. It is required, that the fallback level of the steering system is able to transfer the vehicle into a defined safe state at any time. Therefore, the fallback steering system has not to fulfill the requirements for the failure-free steering system, but the reduced fallback requirements. This reduced performance is called fail degraded.

The maximum required steering torque and steering power determines the minimum steering torque and power the steering system has to produce at least to pass the relevant driving maneuvers in the fail degraded mode. The minimum required steering energy determines the steering system has to provide to reach the safe state even in case of a failure of the power supply.

RESULTS

The maximum occurring steering torque at the pitman arm and the maximum occurring angular velocity at the pitman arm during the different maneuvers are described first. Both parameters are used later to calculate the maximum required steering power and steering energy for each maneuver.

Steering Torque

Figure 1 shows the maximum steering torque and the maximum angular velocity occurring at the pitman arm during the different maneuver. The illustrated values of maximum pitman arm torque and maximum angular velocity of the pitman arm not always occur simultaneously during a maneuver, which is why the product of those two maximum values could be higher than the actual required maximum steering power (see Figure 2).

The maneuver types can be classified into three groups according to their required maximum steering torque. Group A considers the maneuvers requiring less than 600 Nm of torque at the pitman arm. With those maneuvers,

regular driving on the Road Classes 1 and 2 is possible including lane changes, interchanges as well as the driving into a stopping bay. Group B with required steering torques between 600 Nm and 1000 Nm contains the Road Class 3 driving without turning maneuvers, the maneuvers for leaving a highway as well as an avoidance maneuver. The most advanced steering torque requirements between 1000 Nm and 1500 Nm arise for Group C during mountain pass driving, city driving and turning maneuvers.

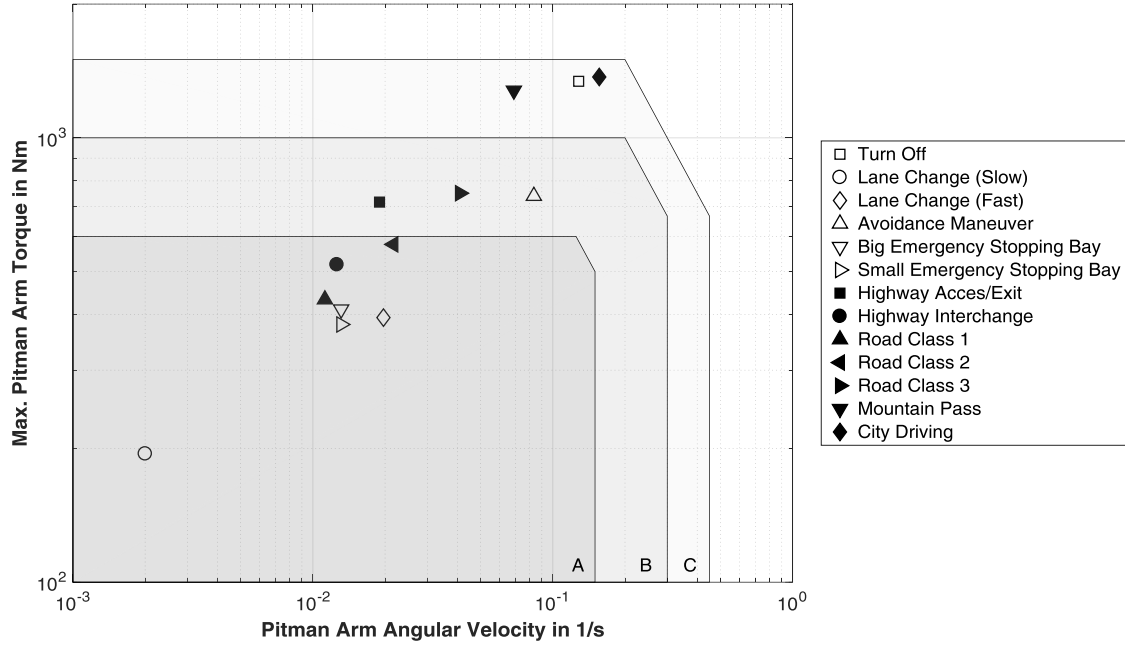


Figure 1. Maximum Occurring Steering Torque T_{Pitman} and Angular Velocity at Pitman Arm δ_{Pitman}

Steering Energy

The energy required for steering during the different driving maneuvers is the measured steering torque at the pitman arm T_{Pitman} integrated over the steering angle at the pitman arm δ_{Pitman} as described in Equation 1:

$$E_{\text{Steering}} = \int T_{\text{Pitman}} d\delta_{\text{Pitman}} \quad (\text{Equation 1})$$

The maneuvers highway driving, country road, mountain pass and city driving are special cases here, since the required energy depends on the driven distance of course. However, to get an indication for the required steering energy during these maneuvers the maximum demanded steering energy on a driving distance of 1 km is used and illustrated with the required steering energy during the other maneuvers in Figure 2.

The classification into the three Groups of driving maneuvers is also feasible for the steering energy. Group A has again the lowest requirements with a required steering energy of less maximum 100 J for the drive of a single maneuver. Between 100 J and 500 J are required by the maneuvers of Group B. Group C requires with between 500 J and 1000 J by far the most steering energy.

Steering Power

The steering power at the pitman arm of the truck occurring during the different driving maneuvers is the derivation of the steering energy E_{Steering} as described in Equation 2:

$$P_{\text{Steering}} = \frac{dE_{\text{Steering}}}{dt} \quad (\text{Equation 2})$$

Figure 2 shows the maximum steering power required during each maneuver type. The maneuver types are classified into three Groups according to the maximum required steering power, similar to the classification in the previous chapters. Group A with the lowest power requirement of maximum 75 W contains the Road Classes 1 and 2, highway interchanges, lane changes and the driving into emergency stopping bays. The highway exit, the avoidance maneuver and the Road Class 3 driving form Group B with a maximum required steering power between 75 W and 150 W. The maneuvers turn-off, mountain pass and city driving requires between 150 W and 300 W of steering power and thus are classified to Group C.

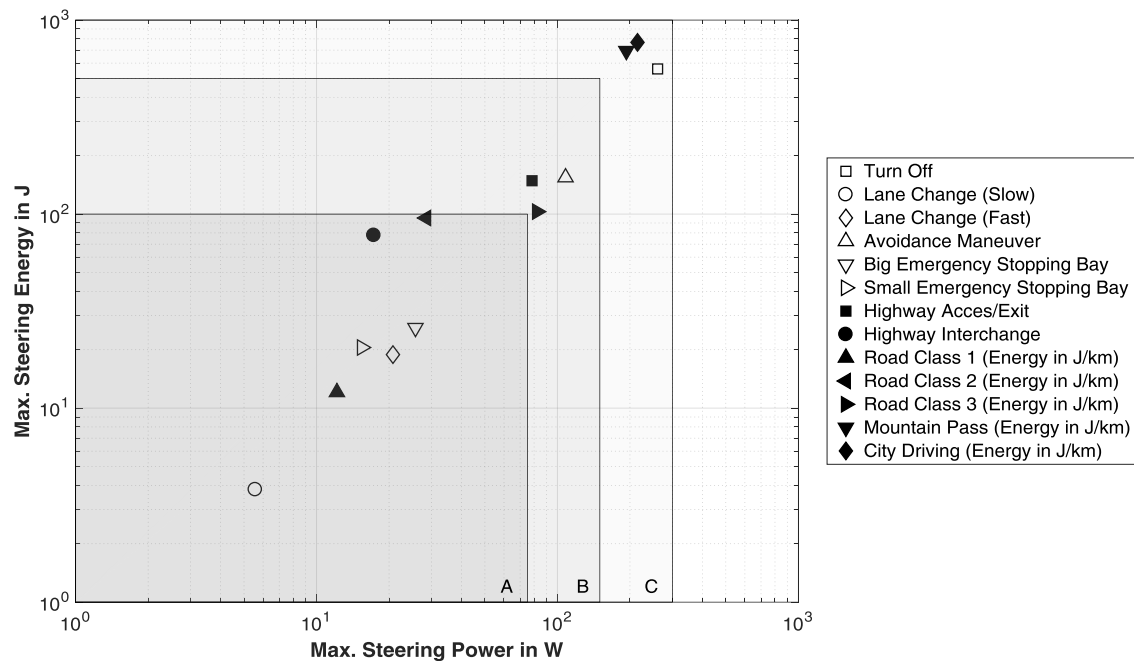


Figure 2. Maximum Steering Power and Maximum Steering Energy

The results from the performed test runs considering the required steering torque, power and energy during the defined relevant maneuvers as well as the classification of these maneuvers into three Groups according their requirements are listed in Table 4. The maneuvers are separated into the three Groups without any overlapping.

Table 4.
Steering Requirement Groups

Group	Maneuver type	$T_{\text{Pitman,max}}$	$P_{\text{Steering,max}}$	$E_{\text{Steering,max}}$
A	Lane change (slow)	< 600 Nm	< 75 W	< 100 J
	Lane change (fast)			
	(Big) Emergency stopping bay			
	(Small) Emergency stopping bay			
	Highway interchange			
	Road Class 1			
	Road Class 2			
B	Avoidance maneuver	600 – 1000 Nm	75 – 150 W	100 J – 500 J
	Highway access/exit			
	Road Class 3			
C	Turn-off to side road (rural roads)	1000 - 1500 Nm	150 - 300 W	500 - 1000 J
	Mountain pass			
	City driving			

Redundancy Requirements

The determined requirements for the different Groups (see Table 3) are used to develop exemplary redundancy requirements for the three different Road Classes and the available 12-t truck. For each Road Class an exemplary combination of maneuvers out of the three different requirement Groups is set up, which are necessary to reach the defined safe state (see Table 4). The exemplary cases are set up according to the worst-case situations for the occurrence of a malfunction, which were found by analysis the roads in the surrounding area of Darmstadt. The torque and power requirements are independent of the amount of necessary maneuvers to reach the safe state. Of course, the required steering energy increase with an increasing amount of necessary maneuvers and with an increasing necessary driving distance.

For the Road Class 1 with a permanent hard shoulder, a worst-case scenario of a failure is, if the malfunction occurs when the truck is on the third lane from the hard shoulder, thus to reach the safe state, three lane changes

are required to stop on the hard shoulder. Because lane changes are not always possible immediately, 1000 m of Road Class 1 driving are considered as well for determining the redundancy requirements. If an avoidance maneuver is necessary as well, the requirements are much higher for this Road Class (see Table 4). The Road Class 2 with emergency stopping bays is quite similar to the Road Class 1, but the difference is, that a safe stop is not possible at any time. A safe stop is only possible at an emergency stopping bay instead, which are only available at a distance of 1000 m. Therefore, to reach a safe state of this Road Class in the worst-case, 2000 m of Road Class 2 driving, two lane changes and the drive into an emergency stopping bay are necessary. The requirements for this class are also much higher, if an avoidance maneuver or another maneuver from Group B is necessary (see Table 4). The Road Class 3 differs from the other two, because there is no safe stop possible at the side of the road. In contrast, a turn-off maneuver is necessary to get to a road where a stop at the side of the road is possible or where the speed limit is below 70 km/h and thus a safe stop in the road is possible. Since a turn to such a road is not possible within a short distance in any case, a 5000 m Road Class 3 drive and a subsequent turn to a side road are considered as relevant to reach a safe state of this class. These maneuvers causes the highest steering redundancy requirements (see Table 5).

Table 5.
Redundancy Requirements

Road Class	Exemplary Maneuvers to reach Safe State	$T_{\text{Pitman,max}}$	$P_{\text{Steering,max}}$	$E_{\text{Steering,max}}$
1	4x Group 1 (add. avoidance maneuver: 1x Group 2)	600 Nm (1000 Nm)	75 W (150 W)	400 J (900 J)
2	5x Group 1 (add. avoidance maneuver: 1x Group 2)	600 Nm (1000 Nm)	75 W (150 W)	500 J (1.00 kJ)
3	5x Group 2 1x Group 3	1500 Nm	300 W	3.50 kJ

CONCLUSION

This paper investigates the redundancy requirements exemplary for a 12-t truck. Therefore, the requirements for a safe state of an automated vehicle are developed with the help of the definitions from the ISO 26262 [5] and [6] (see Table 1). According to German road construction guidelines three different Road Classes are defined according to their different safe states. Several driving maneuvers are determined, which are necessary to reach the different defined safe states (see Table 3).

With the help of driving tests with an available 12-t truck equipped with appropriate measurement equipment, the steering requirements for each of these defined relevant driving maneuvers are recorded and the maneuvers are classified into three groups according their requirements (see Table 4). By combining some of these maneuvers to reach a safe state in an exemplary scenario, the redundancy requirements are calculated for each Road Class (see Table 5).

Although the determined requirements are only exemplary for the used test vehicle and the combinations of maneuvers to reach the safe state are only exemplary as well, it is significant, that the requirements for the Road Class without a hard shoulder or stopping bays are much higher compared to the requirements of the other two Road Classes. Hence, it is concluded that the redundancy requirements for steering systems are much lower, if the automated driven truck only drives on roads with hard shoulders or emergency stopping bays. The fully automated highway driving is such a use case. According to the definition of the safe state in this paper, there are no steering redundancy requirements for inner city automated driving, since an immediate safe stop is possible here at any time. If the truck should be able to drive automated on all types of roads, including on roads with an operation speed above 70 km/h and without hard shoulder or stopping bays, such as country roads, the highest steering fallback steering torque, steering power and steering energy are required.

To determine feasible values for the steering redundancy requirements, an exact definition of the intended use case is necessary to be able to determine the relevant maneuvers to reach the safe state at any time. With this information, the steering requirements necessary for these maneuvers can be used to determine the final steering requirements for this defined use case.

With the help of a simulation model of a truck steering system, including the geometry of the truck's front axle and its tire properties and the trajectory of the described driving tests as an input, it is possible to simulate the required steering torque, power and energy. Such a model is adaptable to calculate the redundancy requirements for other trucks, for example with higher steering axle loads. Of course, not only the axle load, but also the axle geometry and the tire properties has to be adapted to other trucks.

REFERENCES

- [1] Engström, J. et al. 2019. "Deployment of Automated Trucking: Challenges and Opportunities." In Road vehicle automation 5. Springer, Cham, Switzerland, 149–162
- [2] Society of Automotive Engineers. 2016. "Taxonomy and definitions for terms related to on-road motor vehicle automated driving systems." J3016. SAE International
- [3] Herold, M., Said, O. and Winner, H. 2018. "Simulative Assessment of Differential Braking for Steering Redundancy in Automated Driven Trucks." In SIMVEC: Simulation und Erprobung in der Fahrzeugentwicklung, Baden Baden
- [4] Michael Reichenbach. "Interview with Alexander Gaedke: Mit 1000 Parametern für das Lenkgefühl können wir richtig Gas geben." *ATZ Automobiltech Z*, Nr. 6, 22–24 2017.
- [5] International Organization for Standardization. 2011. "Road vehicles - Functional safety - Vocabulary." ISO 26262-1. Schweiz
- [6] Reschka, A. 2017. "Fertigkeiten- und Fähigkeitengraphen als Grundlage des sicheren Betriebs von automatisierten Fahrzeugen im öffentlichen Straßenverkehr in städtischer Umgebung." TU Braunschweig
- [7] Forschungsgesellschaft für Straßen- und Verkehrswesen. 2006. "Richtlinie für die Anlage von Stadtstraßen." RAS 06. FGSV Verlag GmbH, Köln
- [8] Forschungsgesellschaft für Straßen- und Verkehrswesen. 2012. "Richtlinie für die Anlage von Landstraßen." RAL. FGSV Verlag GmbH, Köln
- [9] Forschungsgesellschaft für Straßen- und Verkehrswesen. 2008. "Richtlinie für die Anlage von Autobahnen." RAA. FGSV Verlag GmbH, Köln

APPENDIX

Table 6.
Vehicle Data

Parameter	Value
Total mass	11900 kg
Front axle mass	4340 kg
Wheel base	3.25 m
Track width front axle	1.94 m
Track width rear axle	1.79 m
Tire dimension	245/75 R17.5 134/132 L
Tire pressure	8 bar
$\dot{\delta}_{\text{SteeringWheel}}/\dot{\delta}_{\text{Pitman}}$	16.4 – 18.9
$\dot{\delta}_{\text{SteeringWheel}}/\dot{\delta}_{\text{FrontWheel}}$	12.0 – 20.0

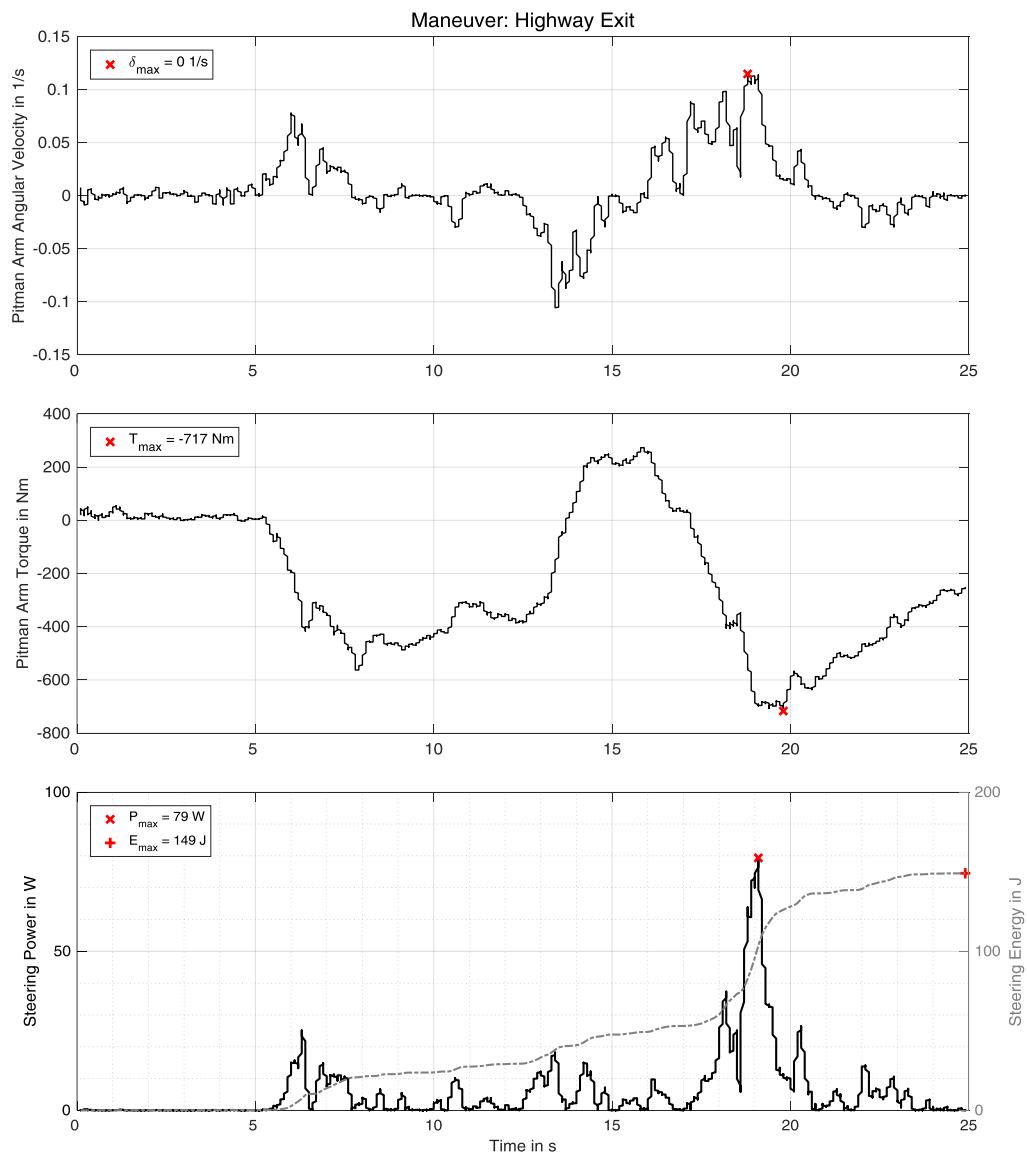


Figure 3. Pitman Arm Angular Velocity, Pitman Arm Torque, Steering Power and Steering Energy exemplary for the Maneuver Highway Exit

**SOCIETAL BENEFIT OF AUTOMATIC EMERGENCY BRAKING AND LANE DEPARTURE
WARNING SYSTEMS IN LARGE TRUCKS**

Jeffrey S. Hickman

Matthew Camden

Alejandra Medina-Flintsch

Richard J. Hanowski

Virginia Tech Transportation Institute

U.S.A.

Brian Tefft, B.²

AAA Foundation for Traffic Safety, U.S.A.

Paper Number: #19-0167

ABSTRACT

The objective of this study was to provide scientifically-based estimates of the societal benefits and costs of two large truck advanced driver assistance systems (ADASs): automatic emergency braking (AEB) and lane departure warning (LDW). For each technology, benefit-cost analyses (BCA) were performed for installing the technology on all large trucks (including retrofitting old trucks) and for equipping new large trucks only, and were performed for equipping only single-unit trucks, only combination-unit trucks, and all large trucks. Sensitivity analyses examined three cost estimates, two estimates of system efficacy, and three discount rates. Equipping trucks with LDW systems were found cost-effective under almost all scenarios examined. Results for AEB were mixed. Only the low cost estimate was cost effective for all large trucks regardless of efficacy rate.

BACKGROUND

Recent advances in large truck advanced driver assistance systems (ADASs) have shown promise to mitigate risky driving behaviors or errors, which in turn help prevent large truck crashes. ADASs may use sensors or alerts to warn a driver of a possible collision, actively assume lateral and/or longitudinal control of a vehicle in situations where a driver does not react to the threat of an imminent crash, or improve driver and fleet management. Two of these large truck ADASs include automatic emergency braking (AEB) systems and lane departure warning (LDW) systems,

AEB systems combine a forward-looking sensor, driver alerts, and automatic vehicle braking. These systems are designed to reduce or prevent rear-end collisions in which the large truck strikes another vehicle (and, to a lesser extent, head-on collisions). LDW systems are vision-based, in-vehicle electronic systems that monitor the vehicle's position within the roadway. Based on lane line markings, the LDW system warns a driver if the vehicle deviates or is about to unintentionally deviate outside the lane line. LDW systems are designed to prevent single vehicle roadway departures, sideswipes, opposite sideswipes, and to a lesser extent, head-on crashes.

Although these large truck ADAS may be effective at preventing large truck crashes, there is limited published data on whether they are cost effective. Despite advancements in the effectiveness of these systems, widespread adoption across the transportation industry is slow. Cost effectiveness data is critical for ADAS as this information may increase industry adoption rates and/or government regulators in mandating their use.

Project Objective

The objective of this project was to provide scientifically-based estimates of the societal benefits and costs (i.e., the impacts an ADAS may have across the entire U.S. society if implemented) of two large truck ADASs, including: AEB systems and LDW systems. To accomplish this objective an Expert Advisory Panel informed cost and benefit estimations for these ADASs so a benefit-cost analysis (BCA) could be performed.

METHODS

An Expert Advisory Panel was held on May 17, 2017. This Advisory Panel consisted of six individuals representing various aspects of the trucking industry, including a representative from a commercial motor vehicle carrier, a trucking insurance company, the Federal Motor Carrier Safety Administration (FMCSA), the National Highway Traffic Safety Administration (NHTSA), an ADAS technology vendor, and an industry safety consultant. The purpose of this meeting was to identify the appropriate efficacy rates and costs for each ADAS and the crash types that may be mitigated or prevented by each of the ADASs. When determining the recommended efficacy rates and cost associated with ADAS, the Advisory Panel prioritized recent research, real-world studies, generation of the technology, Federal regulations, efficacy/cost estimates from the U.S. (due to differences in roadway infrastructure, safety culture, and crash rates), and crash reductions for specific crash types (compared to crash reductions to all large truck crashes). Additionally, the Advisory Panel was

conservative in their efficacy estimates. Following this discussion, upper- and lower-bound efficacy rates and low, average, and high costs were selected for each of the two ADAS (Table 1). The efficacy rates selected by the Expert Panel were applied only to the relevant crash types.

Table 1. Advisory Panel Recommended Relevant Crash Types, Efficacy Rates, and Cost

ADAS	Relevant Crash Types	Efficacy Rates	Costs
AEB	Large truck striking rear-end crashes	16% and 28% ⁽¹⁾	\$500, \$2,500, \$3,000 ⁽²⁻⁴⁾
LDW.	Single vehicle roadway departures, sideswipes, opposite direction sideswipes, and head-on collisions	30% and 47.8% ^(3,5)	\$500, \$1,000, \$1,200 ^(3,6-8)

Benefit Cost Analysis Methods

The BCA followed conventional methods used in similar studies to estimate the societal benefits and costs of implementing ADASs in the trucking industry [1-4]. Societal benefits and costs associated with a reduction in crashes with each ADAS were compared to the costs of deploying each ADAS across the entire U.S. fleet of large trucks over an analysis period of 20 years starting in 2018. The benefits included medical-related costs, emergency response service costs, property damage, lost productivity from roadway congestion, and monetized value of quality-adjusted-life-years lost. Costs considered in this study included the purchase and installation costs associated with the ADAS's hardware, maintenance costs of the ADAS, replacement costs of the ADAS, and costs associated with training drivers to use the ADAS, including driver coaching when applicable.

All costs were calculated using information provided by FMCSA (crash costs), the Bureau of Labor Statistics (training costs), costs provided by carriers and technology providers (hardware costs and training requirements), Ricardo's [5] cost and weight analysis, and the Federal Highway Administration, NHTSA, and the Department of Energy (large truck population, large truck population entering the market, vehicle miles traveled, and vehicle age).

To assess the crash reductions (and their associated costs) of each ADAS, national crash databases were used to identify the target population for each ADAS. These crash databases included the Fatality Analysis Reporting System (FARS) and the General Estimates System (GES). The FARS database was used to determine the number of fatal crashes and their associated fatalities and injuries, and the GES database was used as an estimation for injury and property damage only (PDO) crashes. The GES database also was used to estimate the number of injuries as a result of injury crashes. Queries were developed for each ADAS and information was extracted for different vehicle types for a period of 6 years (2010 to 2015).

When filtering the GES and FARS crashes, the research team carefully considered the scenarios where each ADAS could have mitigated or prevented the crash. Specifically, only rear-end crashes where the large truck struck another vehicle were selected for AEB; all large truck road departures, sideswipes, opposite sideswipes, and head-on crashes were selected for LDW. Additionally, the research team used the following GES/FARS variables to further limit crashes that may have been prevented by each ADAS: pre-event movement, critical event, and first harmful event. Finally, all crashes that involved the use of alcohol or drugs by the large truck driver were eliminated.

Two BCAs were performed for each ADAS. The first analyses included retrofitting the entire U.S. fleet of large trucks with the ADAS. This approach assumed all new trucks added to the fleet are equipped with the ADAS and old trucks are retrofitted with the ADAS. These analyses represents the most benefits, but also the largest costs. The second analyses were an annual incremental costs analysis. This approach assumed all new trucks will be equipped with the ADAS (starting in 2018) and no old trucks are retrofitted. Societal benefits were assessed over the life of the truck for both analyses.

Additionally, analyses were performed on different types of large trucks. The first analysis included all class 7 and 8 trucks (gross vehicle weight rating greater than 26,000 pounds). The second was performed only using class 7 and 8 combination unit trucks (CUTs). The third analysis used class 7 and 8 single unit trucks (SUTs). Finally, separate analyses were performed for each ADAS to account for the rate of monetary discount, in the present value, of the cost and benefits in any future year. Following guidance from the Office of Management and Budget [6] analyses were performed using a 0%, 3%, and 7% discount rate.

RESULTS

The BCA results for each of the ADASs are presented below.

Automatic Emergency Braking Systems

AEB systems were evaluated using a low and high efficacy rate (16% and 28%, respectively) and a low, average, and high cost (\$500, \$2,500, and \$3,000, respectively). Table 2 shows the benefit cost ratios (BCRs) for AEB systems when equipping all trucks (new and old). The analyses with a BCR greater than 1.00 indicate the benefits outweigh the costs (highlighted cells in Table 2). For example, the third row in Table 2 shows the results for all large trucks using a high efficacy rate for AEB systems. When the costs of AEB systems are average and the discount rate is 0%, the estimated costs of AEB systems are 9% greater than the estimated benefits. However, when the costs of AEB systems are low and the discount rate is 0%, the estimated benefits of AEB systems are 3.75 times as great as the estimated costs. Overall, only the low cost estimate was found to be cost effective.

Table 2. BCRs for AEB Systems Installed on New and Old Trucks by Vehicle Type, Efficacy Rate, Cost, and Discount Rate

	Low Cost (\$500)			Average Cost (\$2,500)			High Cost (\$3,000)		
	0%	3%	7%	0%	3%	7%	0%	3%	7%
All Large trucks – 28% Efficacy	3.75	3.58	3.37	0.91	0.87	0.82	0.76	0.73	0.69
All Large trucks – 16% Efficacy	2.14	2.05	1.93	0.52	0.50	0.47	0.44	0.42	0.39
Only CUTs – 28% Efficacy	4.11	3.94	3.72	0.99	0.95	0.90	0.83	0.80	0.76
Only CUTs – 16% Efficacy	2.35	2.25	2.13	0.56	0.54	0.52	0.47	0.46	0.43
Only SUTs – 28% Efficacy	3.08	2.92	2.72	0.75	0.72	0.67	0.63	0.60	0.56
Only SUTs – 16% Efficacy	1.76	1.67	1.56	0.43	0.41	0.38	0.36	0.34	0.32

Table 3 shows the BCRs for AEB systems when only equipping new trucks. As shown in Table 3, a low-cost AEB system was cost effective with a 26% efficacy rate. However, the \$2,500 and \$3,000 AEB system were also cost effective with a 28% efficacy rate.

Table 3. BCRs for AEB Systems Installed on New Trucks Only by Vehicle Type, Efficacy Rate, Cost, and Discount Rate

	Low Cost (\$500)			Average Cost (\$2,500)			High Cost (\$3,000)		
	0%	3%	7%	0%	3%	7%	0%	3%	7%
All Large trucks – 28% Efficacy	6.09	5.67	5.27	1.62	1.49	1.36	1.37	1.26	1.15
All Large trucks – 16% Efficacy	3.48	3.24	3.01	0.92	0.85	0.78	0.78	0.72	0.66
Only CUTs – 28% Efficacy	6.41	5.97	5.54	1.70	1.57	1.43	1.44	1.32	1.21
Only CUTs – 16% Efficacy	3.66	3.41	3.17	0.97	0.89	0.82	0.82	0.76	0.69
Only SUTs – 28% Efficacy	6.09	5.67	5.27	1.62	1.49	1.36	1.21	1.12	1.02
Only SUTs – 16% Efficacy	3.48	3.24	3.01	0.92	0.85	0.78	0.69	0.64	0.58

Lane Departure Warning Systems

LDW systems were evaluated using a low and high efficacy rate (30% and 47.8%, respectively) and a low, average, and high cost (\$500, \$1,000, and \$1,200, respectively). Table 4 shows the BCRs for LDW systems when equipping all trucks (new and old). The results showed that equipping all large trucks or all CUTs with LDW were cost effective regardless of cost, efficacy rate, or discount rate. Additionally, equipping all SUTs with LDW was cost effective with a high efficacy rate regardless of cost or discount rate. However, LDW was only cost effective for SUTs with a low cost.

Table 4. BCRs for LDW Systems Installed on All Trucks by Vehicle Type, Efficacy Rate, Cost, and Discount Rate

	Low Cost (\$500)			Average Cost (\$1,000)			High Cost (\$1,200)		
	0%	3%	7%	0%	3%	7%	0%	3%	7%
All Large trucks – 47.8% Efficacy	4.11	3.92	3.69	2.30	2.20	2.08	1.96	1.88	1.77
All Large trucks – 30% Efficacy	2.62	2.50	2.36	1.47	1.41	1.33	1.25	1.20	1.13
Only CUTs – 47.8% Efficacy	4.83	4.63	4.38	2.70	2.59	2.46	2.29	2.21	2.09
Only CUTs – 30% Efficacy	3.08	2.96	2.79	1.72	1.66	1.57	1.46	1.41	1.33
Only SUTs – 47.8% Efficacy	2.74	2.60	2.43	1.55	1.47	1.37	1.32	1.25	1.17
Only SUTs – 30% Efficacy	1.75	1.66	1.55	0.99	0.94	0.88	0.84	0.80	0.75

Table 5 shows the BCRs for LDW systems when only equipping new trucks. As shown in Table 5, low-, average-, and high-cost LDW systems were cost effective for the lower and upper efficacy rate with all truck types.

Table 5. BCRs for LDW Systems Installed on New Trucks Only by Vehicle Type, Efficacy Rate, Cost, and Discount Rate

	Low Cost (\$500)			Average Cost (\$1,000)			High Cost (\$1,200)		
	0%	3%	7%	0%	3%	7%	0%	3%	7%
All Large trucks – 47.8% Efficacy	6.67	6.21	5.77	3.94	3.65	3.36	3.39	3.13	2.87
All Large trucks – 30% Efficacy	4.26	3.96	3.68	2.52	2.33	2.14	2.16	2.00	1.83

	Low Cost (\$500)			Average Cost (\$1,000)			High Cost (\$1,200)		
	0%	3%	7%	0%	3%	7%	0%	3%	7%
Only CUTs – 47.8% Efficacy	7.53	7.02	6.52	4.45	4.12	3.79	3.83	3.54	3.25
Only CUTs – 30% Efficacy	4.81	4.48	4.16	2.84	2.63	2.42	2.44	2.26	2.07
Only SUTs – 47.8% Efficacy	4.83	4.50	4.18	2.85	2.64	2.43	2.45	2.27	2.08
Only SUTs – 30% Efficacy	3.08	2.87	2.67	1.82	1.69	1.55	1.57	1.45	1.33

DISCUSSION

The current study used efficacy rates from previously published research and identified crashes that may have been prevented through the deployment of an ADAS. Crashes were identified using 2010 to 2015 GES and FARS datasets. BCAs were performed using varying efficacy rates (low and high), vehicle types (all large trucks, only CUTs, and only SUTs), costs (low, average, and high), and discount rates (0%, 3%, and 7%).

Automatic Emergency Braking System Conclusions

The results showed the current pricing/efficacy rate used in this study did not always suggest that AEB systems were cost effective. Only a \$500 AEB system was found to consistently be cost effective regardless of which trucks were equipped with the system. Average and high-cost systems were only found to be cost effective occasionally. Additionally, retrofitting old large trucks with AEB systems typically was not cost effective. These results provide insight into the feasibility of government regulation for large truck AEB systems. There was not a strong case for government regulation requiring AEB systems for the entire U.S. fleet of large trucks given the cost/efficacy rates used in this study. However, the analyses showed AEB systems on new CUTs were cost effective with a high efficacy rate regardless of cost. If the cost and efficacy of AEB systems can be maintained (or improved from) at \$2,500 and 28%, respectively, regulation may be appropriate.

Lane Departure Warning System Conclusions

The results strongly support the cost effectiveness of LDW systems for all large trucks. Regardless of cost and efficacy rate, LDW systems were shown to be cost effective. These results were likely due to: (1) the relatively low cost of LDW systems compared to other ADASs, and (2) the large number/severity of roadway departures, sideswipes, opposite sideswipes, and head-on crashes that could be prevented with LDW systems. As with the other ADASs, cost effectiveness was higher with regulations only for new large trucks. However, these results would support LDW system regulations for both all trucks (retrofitting and original equipment manufacturer installed) and only new large trucks. Mandating LDW on all large trucks (both new and old) would result in the largest benefits in crashes prevented.

- REFERENCES** [1] Hickman, J. S., F. Guo, M. C. Camden, A. Medina, R. J. Hanowski, and E. Mabry. *Onboard Safety System Effectiveness Evaluation Final Report*. Report No. FMCSA-RRT-12-012. FMCSA, U.S. Department of Transportation, 2013.
- [2] Houser, A., D. Murray, S. Shackelford, R. Kreeb, and T. Dunn. *Analysis of Benefits and Costs of Lane Departure Warning Systems for the Trucking Industry*. Report No. FMCSA-RRT-09-022. FMCSA, U.S. Department of Transportation, 2009.
- [3] Murray, D., S. Shackelford, and A. Houser. *Analysis of Benefits and Costs of Forward Collision Warning Systems for the Trucking Industry*. Report No. FMCSA-RRT-09-021. FMCSA, U.S. Department of Transportation, 2009.
- [4] Murray, D., S. Shackelford, and A. Houser. *Analysis of Benefits and Costs of Roll Stability Control Systems for the Trucking Industry*. Report No. FMCSA-RRT-090-020. FMCSA, U.S. Department of Transportation, 2009.
- [5] Ricardo Inc. *Cost & Weight Analysis for CMB and LDWS for Heavy Trucks*. Report No. NHTSA-2011-0066-0085. NHTSA, U.S. Department of Transportation, 2013.
- [6] Office of Management and Budget. *Circular A-4: Regulatory Analysis*. OMB, 2003