SENSOR FUSION: A COMPARISON OF SENSING CAPABILITIES OF HUMAN DRIVERS AND HIGHLY AUTOMATED VEHICLES

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Report No. SWT-2017-12
August 2017

1. Report No. SWT-2017-12	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle Sensor Fusion: A Comparison of Sensing Capabilities of Human Drivers and Highly Automated Vehicles		5. Report Date August 2017
		6. Performing Organization Code 383818
7. Author(s) Brandon Schoettle		8. Performing Organization Report No. SWT-2017-12
9. Performing Organization Name and Address The University of Michigan Sustainable Worldwide Transportation 2901 Baxter Road Ann Arbor, Michigan 48109-2150 U.S.A.		10. Work Unit no. (TRAIS)
		11. Contract or Grant No.
12. Sponsoring Agency Name and Address The University of Michigan Sustainable Worldwide Transportation		13. Type of Report and Period Covered
		14. Sponsoring Agency Code
15. Supplementary Notes Information about Sustainable Worldwide Transportation is available at http://www.umich.edu/~umtriswt.		

16. Abstract

This white paper analyzes and compares the sensing capabilities of human drivers and highly automated vehicles. The key findings from this study are as follows:

• Machines/computers are generally well suited to perform tasks like driving, especially in regard to reaction time (speed), power output and control, consistency, and multichannel information processing.

• Human drivers still generally maintain an advantage in terms of reasoning, perception, and sensing when driving.

• Matching (or exceeding) human sensing capabilities requires autonomous vehicles (AVs) to employ a variety of sensors, which in turn requires complete sensor fusion across the system, combining all sensor inputs to form a unified view of the surrounding roadway and environment.

• While no single sensor completely equals human sensing capabilities, some offer capabilities not possible for a human driver.

• Integration of connected-vehicle technology extends the effective range and coverage area of both human-driven vehicles and AVs, with a longer operating range and omnidirectional communication that does not require unobstructed line of sight the way human drivers and AVs generally do.

• Combining human-driven vehicles or AVs that can "see" traffic and their environment with connected vehicles (CVs) that can "talk" to other traffic and their environment maximizes potential awareness of other roadway users and roadway conditions.

• AV sensing will still be critical for detection of any road user or roadway obstacle that is not part of the interconnected dedicated short-range communications (DSRC) system used by CVs.

• A fully implemented connected autonomous vehicle offers the best potential to effectively and safely replace the human driver when operating vehicles at NHTSA automation levels 4 and 5.

17. Key Words self-driving, autonomous vehicle, human driver, driver performance, sensing, sensors, radar, lidar, connected vehicle, connected autonomous vehicle		18. Distribution Statement Unlimited	
19. Security Classification (of this report) None	20. Security Classification (of this page) None	21. No. of Pages 45	22. Price

Abbreviations used in this report

Abbreviation	Definition
3D	three dimensional
ACC	adaptive cruise control
ADAS	advanced driver-assistance system
AEB	automatic emergency braking
AV	autonomous vehicle
CAMP	Crash Avoidance Metrics Partnership
CAV	connected autonomous vehicle
CIB	crash imminent braking
CV	connected vehicle
DSRC	dedicated short-range communications
GPS	global positioning system
lidar	light detection and ranging
MY	model year
NHTSA	National Highway Traffic Safety Administration
ODI	Office of Defects Investigation
radar	radio detection and ranging
RT	reaction time
V2I	vehicle-to-infrastructure
V2V	vehicle-to-vehicle
V2X	vehicle-to-everything

Contents

Background

Fully autonomous vehicles promise to be able to replace the human driver for most if not all driving situations and scenarios (NHTSA, 2016). To do this efficiently, effectively, and safely requires a multitude of sensors linked to the overall autonomous (also called self-driving or driverless) vehicle system. Not only is it essential that such vehicles accurately know where they are located within the world, they must be equally aware as an alert human driver (but ideally, significantly more aware) of what is physically located around them and what is happening around them. This is no easy task considering the extensive range of fixed objects (signs, light poles, buildings, trees, mailboxes, etc.) and moving objects (vehicles, bicycles, pedestrians, animals, etc.), other roadway users and pedestrians, and environmental conditions (especially severe conditions such as rain, snow, fog, etc.). Adding to this challenge is the fact that most experienced drivers are reasonably capable of anticipating or predicting the behavior of other roadway users and pedestrians (Anthony, 2016; Lee & Sheppard, 2016; MacAdam, 2003).[1] (For additional discussion of these issues, see: Sivak & Schoettle, 2015.)

With 35,092 fatalities on U.S. roadways in 2015, and with 94% of crashes associated with "a human choice or error" (NHTSA, 2016), implementation of safe, successful automated-vehicle technology stands to significantly improve safety on U.S. roads. However, to fully realize substantial improvements in traffic safety will likely require implementation of self-driving technology across all forms of road transportation. For example, in 2015 there were more than 12 million large trucks and buses registered in the U.S., and these vehicle types were involved in crashes resulting in 4,337 fatalities, or about 12% of all traffic fatalities that year (FMCSA, 2017). In addition to automated systems for everyday light-duty passenger vehicles, such systems are also being planned or currently in development for other major road users, including heavy-duty vehicles (Daimler, 2017a; Freedman, 2017), buses (Daimler, 2017b; Walker, 2015), and taxi-like or ride-hailing services (Ohnsman, 2017).

To sense and guide their way through the world, autonomous vehicles (AVs) will use a variety of sensors to accomplish this task, each with their own advantages and disadvantages. Furthermore, certain sensors may be employed to perform multiple tasks. For example, lidar can

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[1] Fitts (1962): "If we understand how a man performs a function, we will have available a mathematical model which presumably should permit us to build a physical device or program a computer to perform the function in the same way (or in a superior manner). Inability to build a machine that will perform a given function as well as or better than a man, therefore, simply indicates our ignorance of the answers to fundamental problems of psychology."

be used for both roadway object detection and 3D mapping of the environment to assist in geolocation (Kent, 2015); camera systems can be used for both roadway object detection as well as assisting in identifying current environmental and roadway conditions. Figures 1 and 2 show examples of such dual applications for lidar; Figure 1 shows the detection of several roadway objects, while Figure 2 shows example data from a recent roadway-mapping application. The relative importance of effectively incorporating information from all available sensors (*sensor fusion*) to inform the decision-making process for AVs will only continue to grow as such vehicles move closer to fully automated operation.
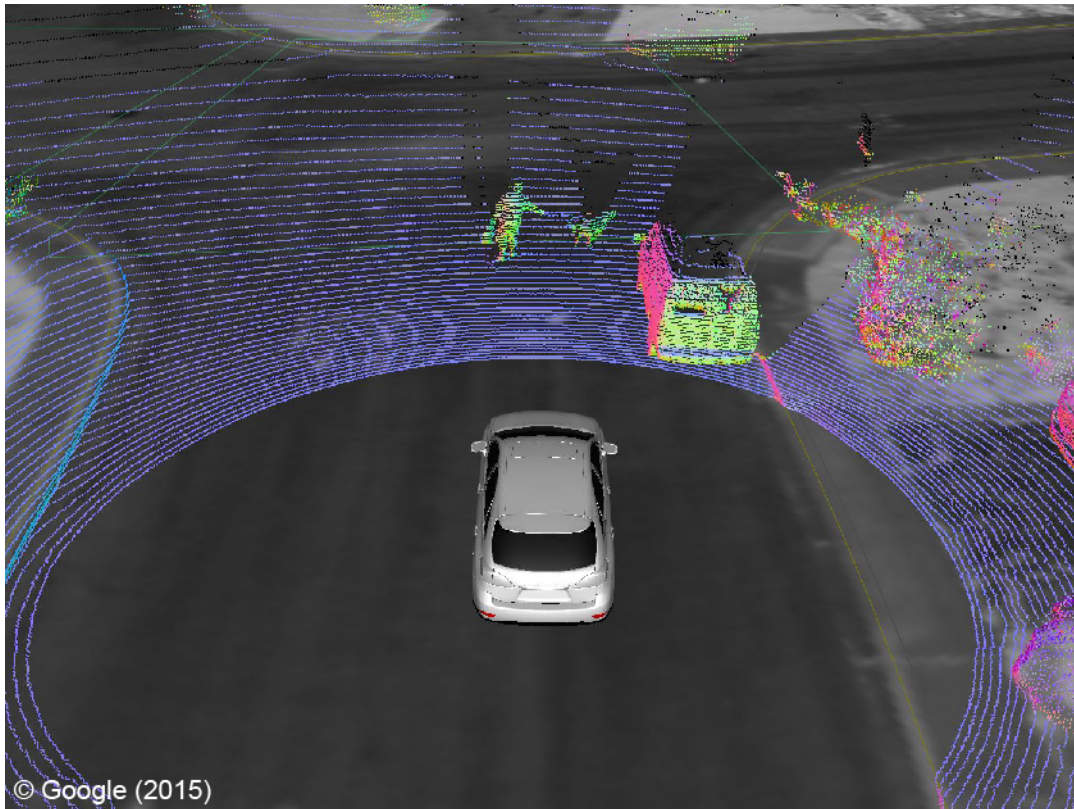

Figure 1. Pedestrian, dog, and parked vehicle, as seen by lidar on a Google self-driving vehicle (Google, 2015).
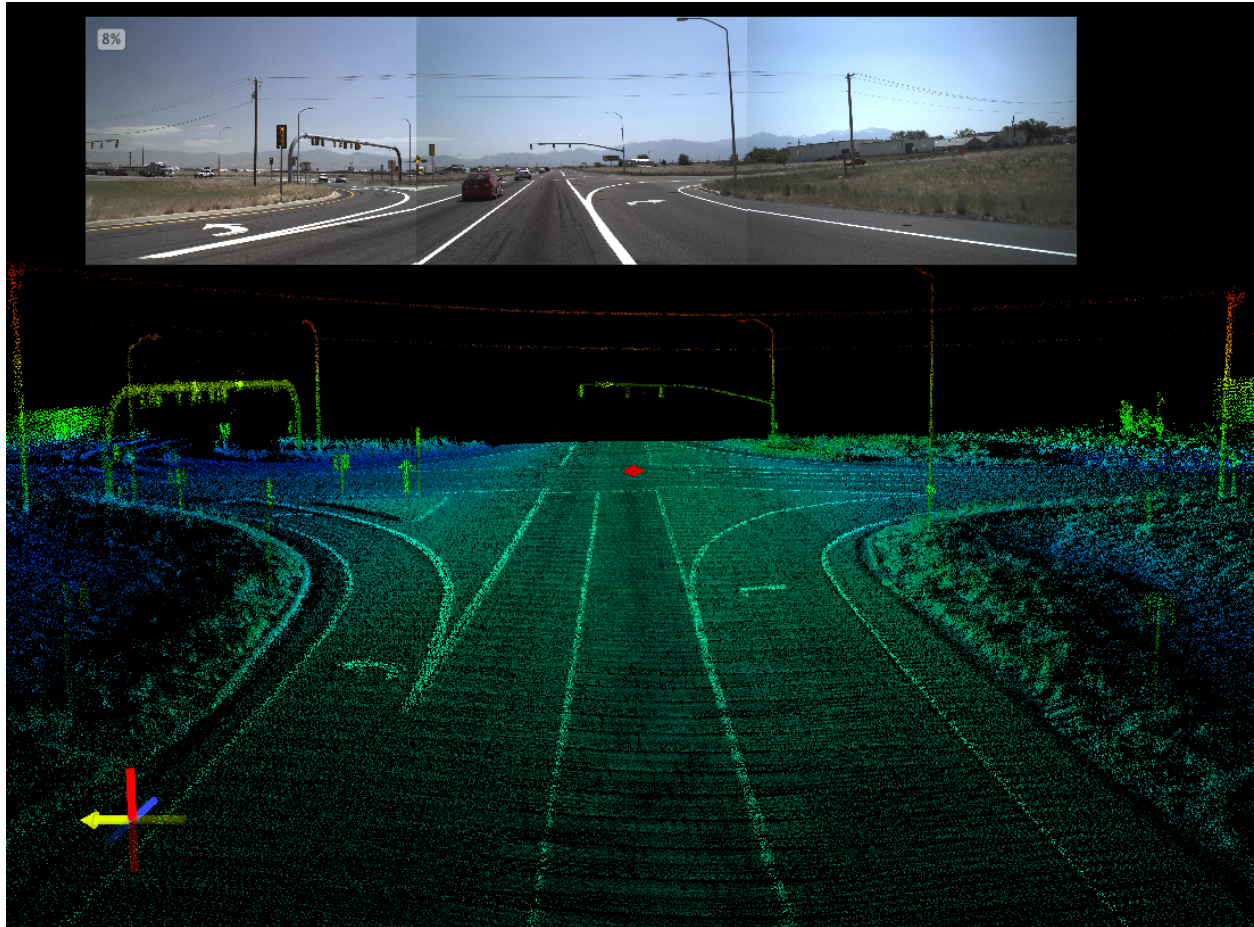
Figure 2. Lidar image and corresponding photographic image collected as part of the Roadway Imaging and Inventory program commissioned by the Utah DOT (Utah DOT, 2013).

This report includes a broad examination of the current sensing capabilities of such vehicles, as well as the humans they promise to replace. A comparison will be made of the general performance capabilities and limitations of human drivers, automated vehicles (AV), connected vehicles (CV), and connected automated vehicles (CAV). For the purposes of discussion in this report, automated vehicles can include both human-driven vehicles supported by advanced driver-assistance systems (ADAS) operating at NHTSA automation levels 1 or 2 (see below), as well as fully automated vehicles (i.e., autonomous, driverless, self-driving [Godsmark, 2017]) operating at automation level 3 or higher.

Figure 3 presents a summary of the current levels of vehicle automation, including the corresponding levels of required driver engagement, available driver support, and overall responsibility for monitoring the driving task and controlling the vehicle (adapted, in part, from

NHTSA, 2016). (Connected-vehicle technology, discussed later in this report, is not shown in Figure 3 as it does not require automation of the vehicle, and as such can be applied to vehicles operating at any automation level.)   Based on the automation levels described in Figure 3, effective and reliable sensing is important for vehicles as low as level 1, and must undoubtedly be perfected for vehicles operating at levels 4 and 5, where a driver may not even be present.

Automation level:	0	1	2	3	4	5
Description:	No automation	Driver assistance	Partial automation	Conditional automation	High automation	Full automation
Driver engagement:	Responsible for all driving	Hands -or- feet off	Hands + feet off (partial)	Eyes off	Brain off (or driver not even present)	
Driver support:	none	Advanced driver-assistance systems (ADAS)			only when or if human driven	
Monitors driving:	Human driver			Automated system		
Vehicle control:	Human driver		Shared	Automated system		

Figure 3. Summary of the current levels of vehicle automation, including the corresponding levels of required driver engagement, available driver support, and overall responsibility for monitoring the driving task and controlling the vehicle (adapted, in part, from NHTSA, 2016).

Comparisons of current performance characteristics for the primary sensors required to enable all-around vehicle operation in all conditions will be examined for the following types of sensors: [2]

- Human eyes
- Radar
- Lidar
- Camera systems
- Dedicated short-range communications (DSRC) for connected vehicles

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[2] Detailed discussion of how each sensor physically operates or functions will not be covered in this report.

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(Ultrasonic and other short-range sensors are not included in this analysis as they are nearly exclusively used for low-speed applications such as parking, and are not as critical to safe vehicle operation at moderate to high speeds as the other sensors examined here. Similarly, while GPS is integral to geolocation for navigation, it is not a sensor applicable to the discussion in this report.)

Key performance aspects

Common limitations

There are several shared limitations affecting each driver or vehicle type. The following list, though not exhaustive, identifies some of the most common performance limitations and related causes:

- Extreme weather (heavy rain, snow, or fog): Reduces maximum range and signal quality (acuity, contrast, excessive visual clutter) for human vision, AV visual systems (cameras, lidar), and DSRC transmissions (though to a lesser extent).

- Excessive dirt or physical obstructions (such as snow or ice) on the vehicle: Interferes with or reduces maximum range and signal quality (acuity, contrast, physical occlusion of field of view) for human vision and all basic AV sensors (cameras, lidar, radar).

- Darkness or low illumination: Reduces maximum range and signal quality (acuity, contrast, possible glare from external light sources) for human vision and AV camera systems.

- Large physical obstructions (buildings, terrain, heavy vegetation, etc.): Interferes with line of sight for human vision and all basic AV sensors (cameras, radar, lidar); some obstructions can also reduce the maximum signal range for DSRC.

- Dense traffic: Interferes with or reduces line of sight for human vision and all basic AV sensors (cameras, radar, lidar); can also interfere with effective DSRC transmission caused by excessive volumes of signals/messages. (However, human drivers do have some limited ability to see through the windows of adjacent vehicles.)

Relative strengths of human drivers and automated vehicles

A topic of frequent discussion when designing a system combining human and machine relates to the question of which tasks are performed best by whom (human versus machine). (For the purposes of this discussion, the term *machine* also encompasses computer systems and combined computer/mechanical systems such as automated vehicles.) A classic analysis by Fitts (1951) outlined the major categories of strengths and weaknesses for each side of the human-machine interaction relationship (i.e., ideal function allocation) (also see: Cummings, 2014; de Winter & Dodou, 2014). Table 1 shows a summary of the so-called Fitts list (adapted from Cummings, 2014; de Winter & Dodou, 2014).

Table 1
Summary of Fitts list of strengths and weaknesses across various aspects of
function allocation between humans and machines/computers
(adapted from Cummings, 2014; de Winter & Dodou, 2014).

Aspect	Human	Machine/computer
Speed	Relatively slow	Fast
Power output	Relatively weak, variable control	High power, smooth and accurate control
Consistency	Variable, fatigue plays a role, especially for highly repetitive and routine tasks	Highly consistent and repeatable, especially for tasks requiring constant vigilance
Information processing	Generally single channel	Multichannel, simultaneous operations
Memory	Best for recalling/understanding principles and strategies, with flexibility and creativity when needed, high long-term memory capacity	Best for precise, formal information recall, and for information requiring restricted access, high short-term memory capacity, ability to erase information after use
Reasoning	Inductive and handles ambiguity well, relatively easy to teach, slow but accurate results, with good error correction ability	Deductive and does *not* handle ambiguity well, potentially difficult or slow to program, fast and accurate results, with poor error correction ability
Sensing	Large, dynamic ranges for each sense, multifunction, able to apply judgement, especially to complex or ambiguous patterns	Superior at measuring or quantifying signals, poor pattern recognition (especially for complex and/or ambiguous patterns), able to detect stimuli beyond human sensing abilities (e.g., infrared)
Perception	Better at handling high variability or alternative interpretations,[3] vulnerable to effects of signal noise or clutter	Worse at handling high variability or alternative interpretations,[3] also vulnerable to effects of signal noise or clutter

Similarly, each driver or technology has unique strengths and weaknesses, and no single driver or vehicle type is distinctly superior to all other systems. The following subsections highlight and describe the main performance aspects and advantages of the important sensors

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[3] Hence the continued effectiveness of CAPTCHA challenge-response as a security measure to differentiate humans from computers (CAPTCHA, 2017).

associated with each driver or technology.[4] While the specific focus of these sections is light-duty passenger vehicles, automated heavy-duty vehicles employ the same types of sensors, with generally the same performance characteristics (Daimler, 2014).

Human drivers

Eyes

- Color, stereo (binocular) vision with depth perception
- Large, dynamic range
- Wide field of view, moveable both horizontally and vertically
- Field of view (horizontal): ~ 120° for binocular vision
- Range: No specific distance limit[5] (mainly limited by an object's contrast and projected size on the retina); realistic daytime limit of at least 1000 m (3280 ft) and a realistic nighttime limit of 75 m (about 250 ft) under typical U.S. low-beam headlamp illumination (both distances are applicable for a pedestrian or an object in the roadway)
- Resolution: ~ 0.02°

Autonomous vehicles (AV)

Radar

- Accurate distance information
- Relatively long range
- Robust in most weather conditions, can be hidden or protected behind body panels
- Immune to effects of illumination or darkness
- Fixed aim and field of view, but able to employ multiple radar sensors as needed
- Field of view (horizontal): ~ 15° (long range) to ~ 90° (short range)
- Range: ~ 250 m
- Resolution: ~ 0.5° to ~ 5°

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[4] Information in this section was derived from the following sources: AASHTO (2001), Bhise (2012), Bosch (2009), Boyce (2014), Continental (2017), CVEL (2017), Dickmann, et al. (2015), Falson (2014), Ford (2017), Hammerschmidt (2013), Hyundai (2016), Keeney (2011), Krok (2016), LeddarTech (2016), Lee & Lim (2013), McDonald (2015), NHTSA (2017c), NSC (2017), Owsley and McGwin (2010), Pleskot (2016), de Ponte Müller (2017), Quanergy (2015), RITA (2016), Rosenholtz, Li, & Nakano (2007), Schoettle & Flannagan (2011), Sivak, Schoettle, Reed, & Flannagan (2007), and Sommer, Eckhoff, & Dressler (2013).

[5] To illustrate this point, consider that the most distant target generally visible to the naked eye is the Andromeda galaxy, at a distance of roughly 2.5 million light years, or approximately 24 quintillion km (15 quintillion miles) (Burress, 2007).

Lidar

- Accurate distance and size information

- Able to discern high level of detail (shape, size, etc.), especially for nearby objects and lane markings

- Useful for both object detection and roadway mapping

- Immune to effects of illumination or darkness

- Fixed aim and field of view, but able to employ multiple lidar sensors as needed (although some lidar systems are capable of 360° within a single piece of equipment)

- Field of view (horizontal): 360° (maximum)

- Range: ~ 200 m

- Resolution: ~ 0.1°

Camera systems

- Color vision possible (important for sign and traffic signal recognition)

- Stereo vision when using a stereo, 3D, or time-of-flight (TOF) camera system

- Fixed aim and field of view, but able to employ multiple cameras as needed

- Field of view (horizontal): ~ 45° to ~ 90°

- Range: No specific distance limit (mainly limited by an object's contrast, projected size on the camera sensor, and camera focal length), but realistic operating ranges of ~ 150 m for monocular systems and ~ 100 m (or less) for stereo systems are reasonable approximations

- Resolution: Large differences across different camera types and applications

Connected vehicles (CV)

Dedicated short-range communications (DSRC)

- Applicable to vehicles operating at any automation level

- No line-of-sight requirement (omnidirectional antenna)

- Robust in weather conditions

- Able to both receive and send detailed information

- Range: Long range (~ 500 m) that can be effectively extended by communicating with transportation infrastructure in addition to other vehicles; however, the signal strength of transmissions decrease based on the inverse-square law (i.e., signal strength is inversely proportional to the square of the distance from the transmitter)

- Can communicate future actions or planned maneuvers (especially for AVs) to other traffic, alleviating need for other traffic to sense and/or predict what the connected vehicle will do

- Can communicate information about recently encountered roadway conditions, traffic conditions, etc. to other roadway users

- Able to communicate with other road users or transportation modes within the interconnected DSRC system (e.g., pedestrians, trains, etc.)

Table 2 summarizes the key operating characteristics of each sensor for human-driven vehicles, autonomous vehicles (AV),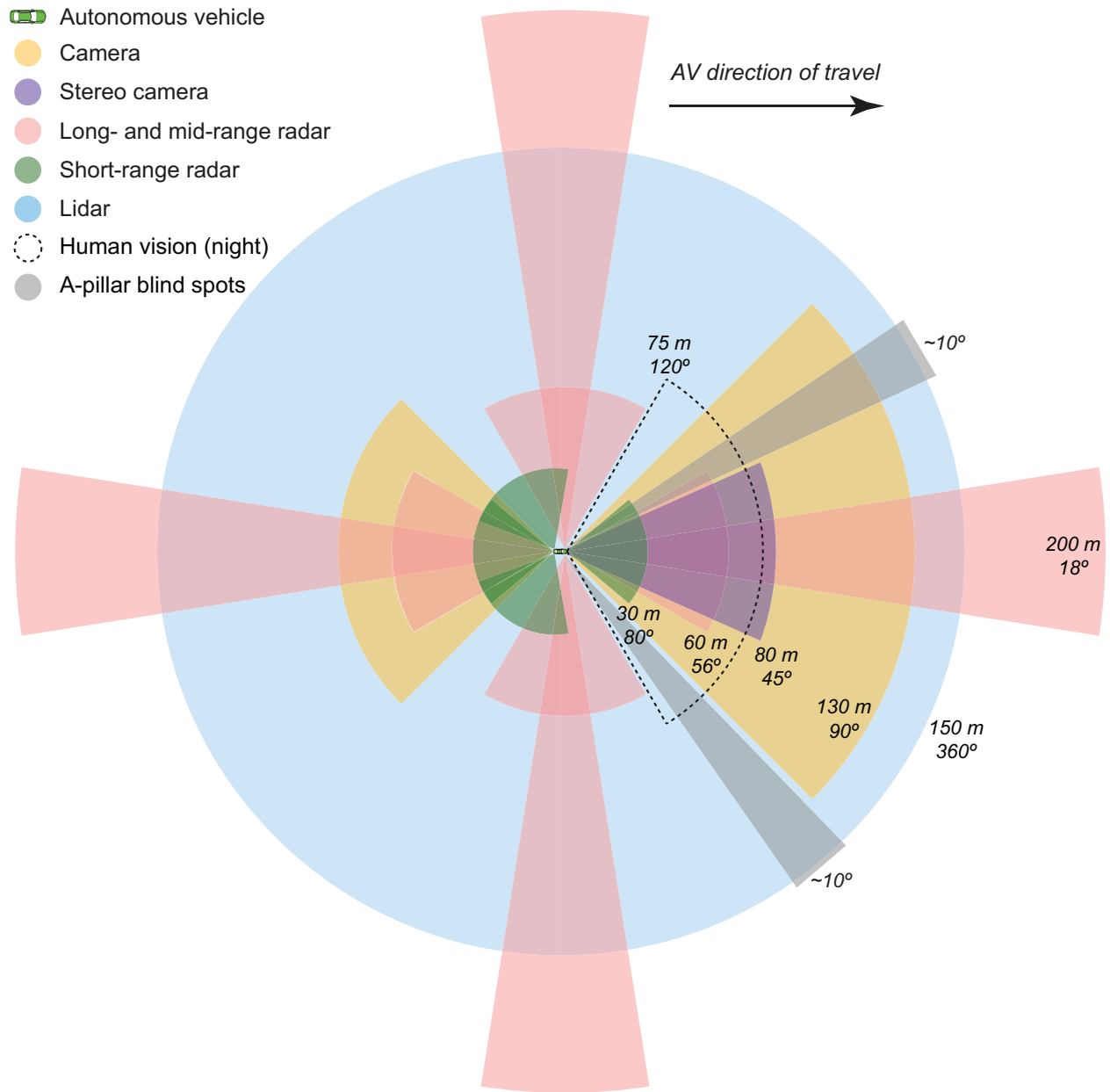 connected vehicles (CV), and a connected autonomous vehicle (CAV). Figure 4 shows an example (drawn to scale) for various sensors, with reasonable estimates of coverage area (field of view) and typical operating ranges, for 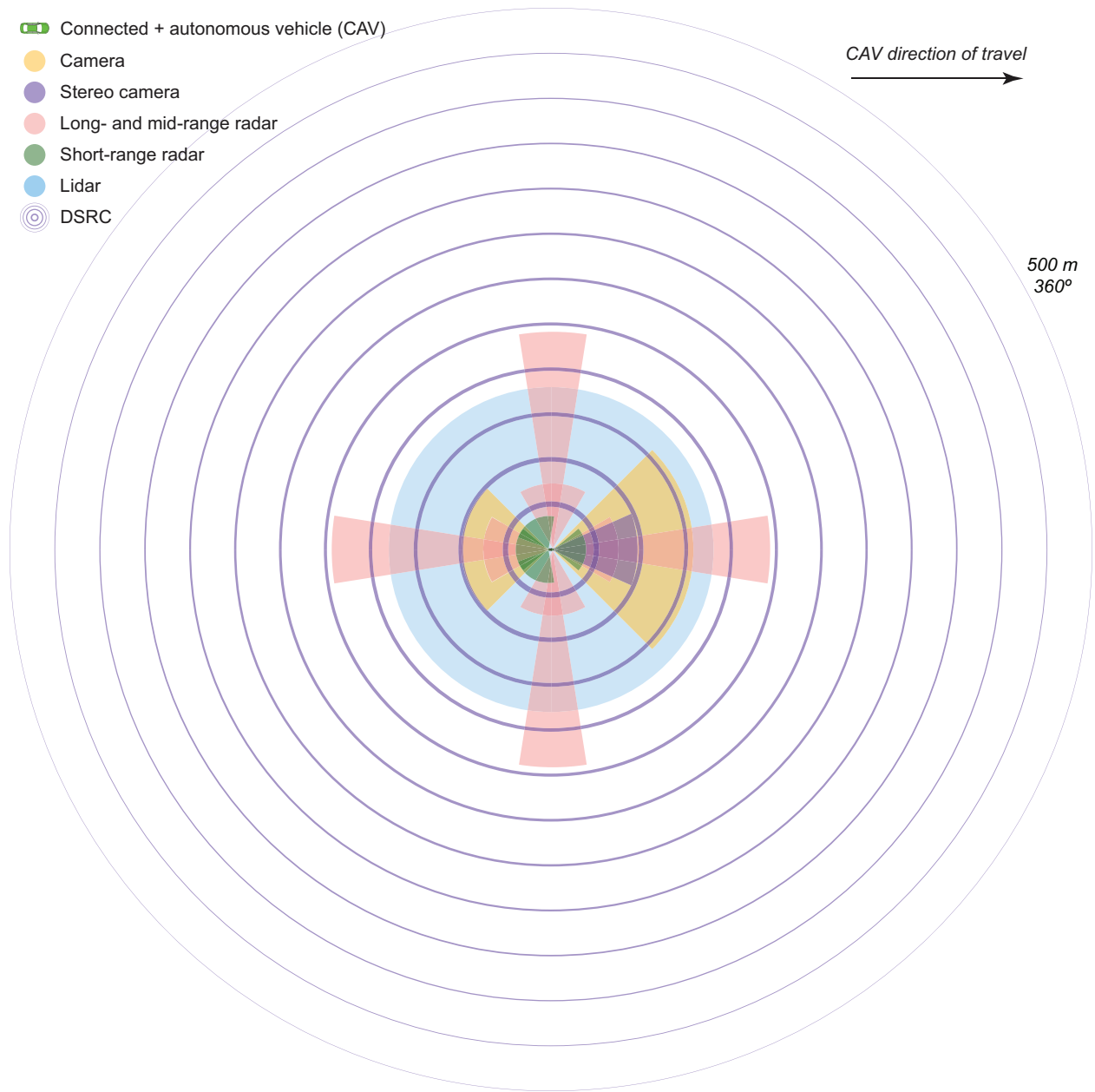both a human-driven vehicle as well as a hypothetical AV. (The A-pillar blind spots shown for human drivers do not have any specific range limit. Due to the very long range of human daytime vision, it has been excluded from the diagrams in this report.) The specific sensor layout shown in Figure 4 is based on a combination of published specifications and descriptions of state-of-the-art ADAS and AV configurations.[6] Actual sensor locations, types, ranges, and other aspects of full implementation on a real-world AV may vary from those shown here. As such, the specifications shown in Figure 4 illustrate one possible example, and should be treated as approximations only. Although Figure 4 shows reasonable performance parameters for AV sensors, specific sensor designs and implementations will ultimately determine the in-situ performance parameters for a specific AV in the real world. Figure 5 illustrates the omnidirectional, extended range (drawn to scale) afforded by the addition of DSRC for a connected autonomous vehicle (CAV) employing DSRC to supplement the sensor suite employed by the AV-only functions. The vehicles shown in the figures in this report correspond to an average-sized U.S. sedan, approximately 5 m long by 1.9 m wide (approximately 200 inches long by 75 inches wide).

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[6] The specific implementation illustrated in this report, though not identical, closely resembles that of the Mercedes-Benz S-Class research autonomous vehicle known as Bertha (Dickmann, et al., 2015).

Table 2
Summary of the key operating characteristics of each sensor as they apply to autonomous
vehicles. (AV sensor performance summary adapted, in part, from WCP, 2016.)

Performance aspect	Human	AV			CV	CAV
		Radar	*Lidar*	*Camera*	*DSRC*	*CV+AV*
Object detection	Good	Good	Good	Fair	n/a	Good
Object classification	Good	Poor	Fair	Good	n/a	Good
Distance estimation	Fair	Good	Good	Fair	Good	Good
Edge detection	Good	Poor	Good	Good	n/a	Good
Lane tracking	Good	Poor	Poor	Good	n/a	Good
Visibility range	Good	Good	Fair	Fair	Good	Good
Poor weather performance	Fair	Good	Fair	Poor	Good	Good
Dark or low illumination performance	Poor	Good	Good	Fair	n/a	Good
Ability to communicate with other traffic and infrastructure	Poor	n/a	n/a	n/a	Good	Good

Figure 4. Example illustration (drawn to scale) of the various sensors, with reasonable estimates of coverage area (field of view) and typical operating ranges, for both a human-driven vehicle as well as a hypothetical AV.

Figure 5. Typical sensor ranges (drawn to scale) for a connected autonomous vehicle (CAV) employing DSRC to supplement the sensor suite employed by the AV-only functions, illustrating the omnidirectional, extended range afforded by the addition of DSRC.

Illustrative case studies

Assumptions

The following case studies present a variety of scenarios and vehicle maneuvers, and all analyses and calculations assume ideal conditions unless otherwise described. The ideal conditions assumed are as follows:

- All vehicles and tires are in proper working order.

- The human driver is alert and rested, skilled/experienced, and has good color vision with good visual acuity (i.e., 20/20).

- Human drivers have clear fields of view and AV sensors are clean and functioning properly. This includes having an unobstructed line of sight (if needed) when discussing detection distances.

- Both the human driver and AV system will make the appropriate decision for the given scenario.

- Both the human driver and AV system will be capable of controlling the vehicle when performing the required maneuver.

- The analyses to follow will discuss performance *capabilities* of humans and automated vehicles, but not the associated *probabilities* of each level of performance occurring.

Minimum stopping distance

The minimum stopping distance for a vehicle is dependent upon the reaction time of the driver (human or automated), the speed of the vehicle, and the minimum braking distance for that specific vehicle under the current roadway conditions (e.g., dry, wet, snowy, etc.). For scenarios involving maximum braking (to achieve the minimum braking distance), the main variable in the minimum stopping distance for each driver type is reaction time.

Calculations of minimum stopping distances were performed for four scenarios involving two extreme roadway conditions (dry and wet) and two driver types (human drivers and automated vehicles operating at level 2 or higher). For each set of roadway conditions and driver

types, minimum stopping distances were calculated for speeds ranging from 35 km/h (22 mph) to 240 km/h (149 mph).[7] Calculations for all scenarios assume a straight, flat roadway.

The varying inputs for the four scenarios are listed below:

- Ideal conditions (human): dry road ($\mu = 0.8$), faster reaction time (1.6 s)

- Ideal conditions (AV): dry road ($\mu = 0.8$), faster reaction time (0.5 s)

- Degraded conditions (human): wet road ($\mu = 0.4$), slower reaction time (2.5 s)

- Degraded conditions (AV): wet road ($\mu = 0.4$), slower reaction time (0.75 s)

The friction coefficients used in these calculations are intended to represent a reasonable range of conditions, corresponding to ideal (dry, $\mu = 0.8$) and degraded (wet, $\mu = 0.4$) traction on straight, flat, asphalt and concrete roads (AASHTO, 2001; Bosch, 2011; Greibe, 2007). While the friction coefficient can often be worse than 0.4 under very wet, snowy, or icy conditions, it is less likely to be significantly better than 0.8 for dry roads (Bosch, 2011). The two reaction times selected for these calculations correspond to (1) reasonably fast reaction times and (2) slower reaction times for a human driver to *unexpected* hazards[8] (AASHTO, 2001; Olson and Sivak, 1986). Due to a lack of published data regarding AV reaction times, estimates were used for faster and slower AV reaction times based on conversations with individuals who are familiar with AV design and performance. However, reaction times can be highly variable and difficult to predict for all situations, so the values used here are reasonable approximations only.

The specific equations used to perform the minimum stopping distance calculations are shown in the Appendix, including an example calculation for a vehicle traveling at 80 km/h (50 mph) on a dry road with a reasonably fast human-driver reaction time. Results for all four scenarios and for speeds ranging from 35 km/h to 240 km/h (22 mph to 149 mph) are shown in the Appendix, in Figures A1 through A6. Stopping distances are shown in meters (left y-axis) and in feet (right y-axis).

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[7] While the top speed of 240 km/h (149 mph) for the current calculations significantly exceeds the highest current highway speed limits in most countries including the United States (the highest posted speed limit in the United States is in Texas at 85 mph or about 140 km/h [Texas DOT, 2017]), countries such as Germany do allow vehicles to travel at these speeds (or higher) on some sections of highway (i.e., the Autobahn). The decision to select 240 km/h as the top speed was based on the fact that some manufacturers allow adaptive cruise control (ACC) to be set at such high speeds (Audi, 2016; Mercedes-Benz, 2017), combined with the frequent practice of electronically limiting top speeds to 250 km/h (155 mph) or less (Popa, 2012).

[8] Human drivers generally have slower reaction times for unexpected hazards than for expected hazards (AASHTO, 2001; Olson & Sivak, 1986). However, the concept of expectation (as it applies to human drivers) should have no effect on AV sensing and reaction time.

Based on the calculated results of these minimum-stopping-distance scenarios, Table 3 shows the maximum speeds that would still allow the applicable sensors for each vehicle type to detect a worst-case scenario (i.e., one that requires braking to a full stop as the only possible response or maneuver) with enough safe stopping distance to avoid an obstacle or situation, under the dry and wet conditions described earlier. The results in Table 3 account for the corresponding range and reaction-time limitations of each vehicle-and-sensor combination (human, AV, or CAV), with the distances corresponding to the longest-range sensor available on each vehicle type.

Table 3
Maximum speed allowing for minimum stopping distance within the range limitations of each vehicle type and sensor combination.

Vehicle type (longest range sensor) [range limit]	Ideal conditions (dry, faster reaction)	Degraded conditions (wet, slower reaction)
Human driver (eyes) [night: 75 m]	85 km/h (53 mph)	60 km/h (37 mph)
AV (radar) [250 m]	210 km/h (130 mph)	145 km/h (90 mph)
CAV (DSRC) [500 m]	305 km/h (190 mph)	215 km/h (134 mph)
Human driver (eyes) [day: 1000 m]	405 km/h (252 mph)	285 km/h (177 mph)

Based on the same calculated results from the minimum-stopping-distance scenarios, Table 4 shows the maximum speeds that would still allow an ADAS-equipped (level 2) or semiautonomous (level 3) vehicle to safely alert the driver, with varying levels of preview before being required to take over and drive (10 s, 20 s, or 30 s). As in the previous table, each speed listed assumes a worst-case scenario (i.e., one that requires braking to a full stop as the only possible response or maneuver) with enough safe stopping distance for the driver to respond to avoid an obstacle or situation *after* the corresponding preview time, under the same dry and wet conditions modeled earlier. (It is possible that drivers might respond significantly faster or slower than the selected preview times under real-world conditions.) The results in Table 4 account for the corresponding limitations of each vehicle and sensor combination (human, AV,

or CAV), with the distances corresponding to the longest-range sensor available on each vehicle type.

Table 4
Maximum speed allowing for minimum stopping distance within the range limitations of each vehicle type and sensor combination corresponding to various preview times for the driver before being required to take control.

Preview time before required takeover	Vehicle type	Ideal conditions (dry, faster reaction)	Degraded conditions (wet, slower reaction)
10 s	AV (radar @ 250 m)	75 km/h (47 mph)	65 km/h (40 mph)
	CAV (DSRC @ 500 m)	135 km/h (84 mph)	120 km/h (75 mph)
20 s	AV (radar @ 250 m)	40 km/h (25 mph)	40 km/h (25 mph)
	CAV (DSRC @ 500 m)	80 km/h (50 mph)	75 km/h (47 mph)
30 s	AV (radar @ 250 m)	< 35 km/h (< 22 mph)	< 35 km/h (< 22 mph)
	CAV (DSRC @ 500 m)	55 km/h (34 mph)	55 km/h (34 mph)

Blind spots, sensor coverage, and sensor fusion

Blind spots and sensor coverage

Sensor blind spots can occur because of (1) obscured line of sight or (2) gaps or limits in sensor coverage. Gaps or limits in sensor coverage include situations with no sensor coverage due to general range limitations of the system, and situations when certain areas or objects are visible to only one sensor, either temporarily (e.g., only within range of one sensor type) or permanently (e.g., only one sensor is capable of detecting a particular object or condition, such as fog).

For line-of-sight obstructions, Figure 6 illustrates the ability of a small number of vehicles—just two additional vehicles are shown in the figure, one ahead and one adjacent—to block the line of sight needed for conventional AV sensors to operate, creating large blind spots in sensor coverage. Figure 7 illustrates the ability of a connected autonomous vehicle (CAV) to

overcome this problem with omnidirectional DSRC, which does not require line of sight to communicate. (For automated heavy-duty vehicles, some of this problem might be alleviated by the higher placement of sensors, taking advantage of the height afforded by such vehicles.)
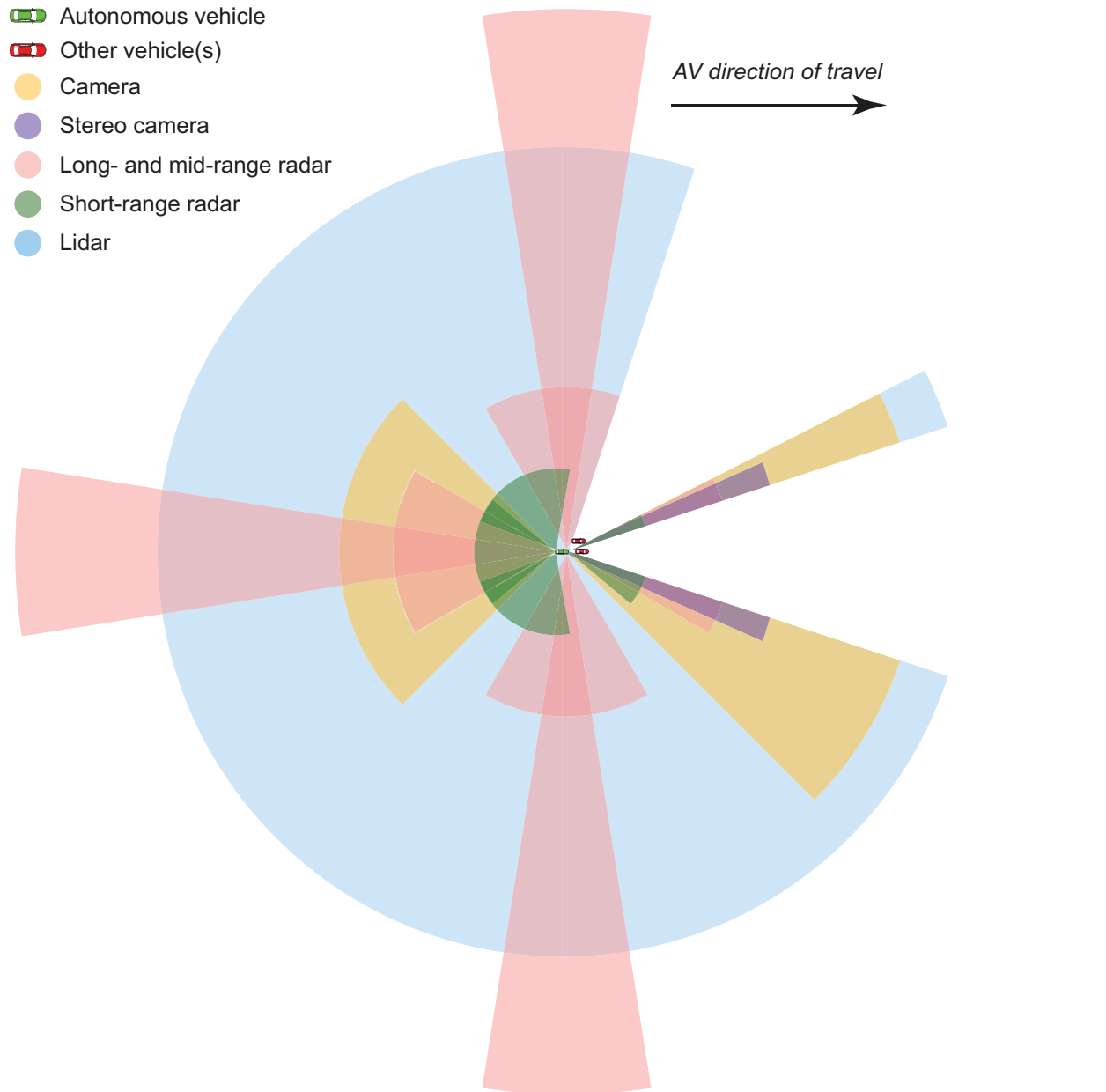

Figure 6. Example illustration of the line-of-sight obstructions (unshaded regions) for the AV sensors that are created by adjacent vehicles in traffic.
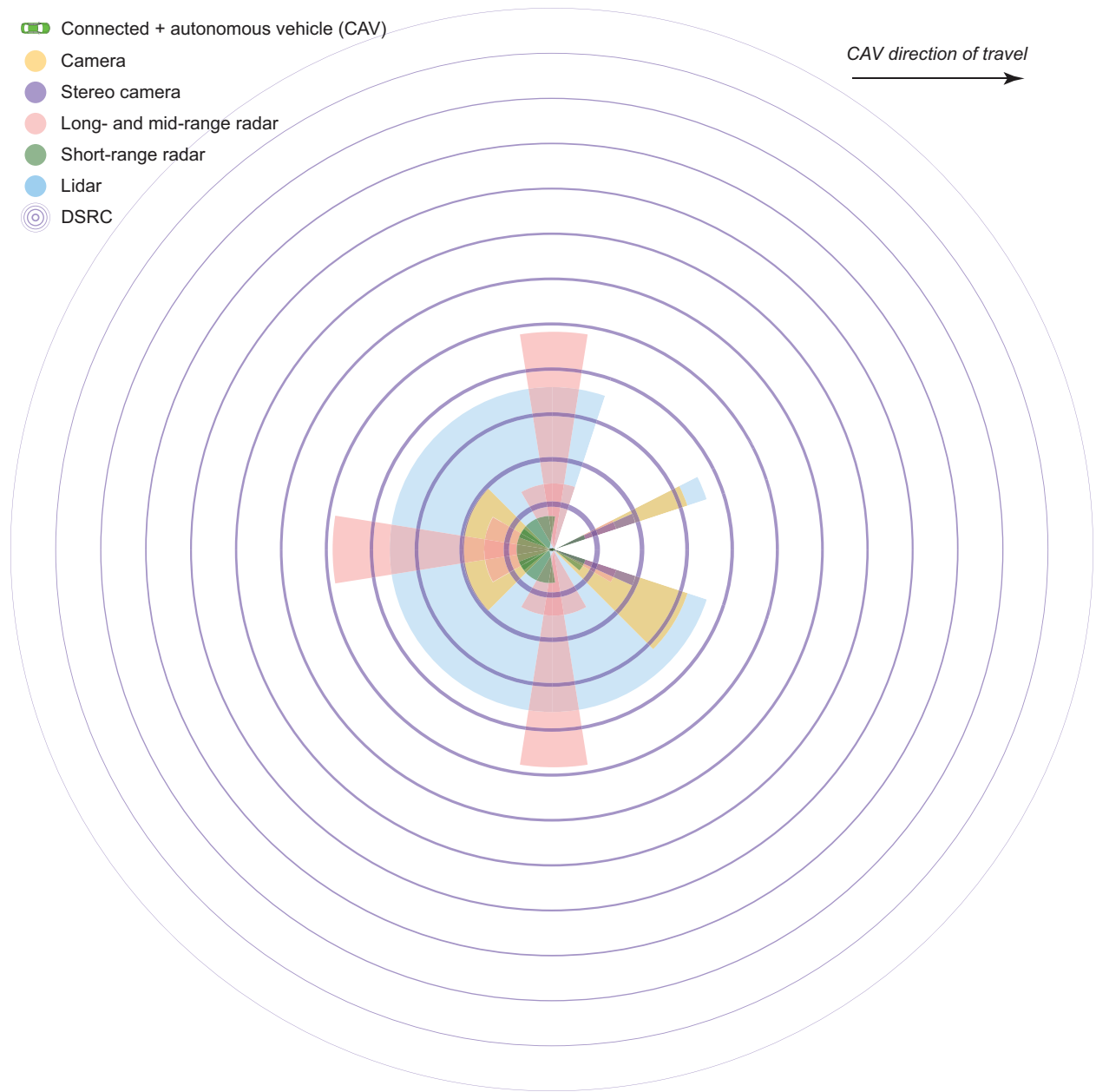
Figure 7. Example illustration of the ability of a connected autonomous vehicle (CAV) to overcome the line-of-sight obstruction problem with omnidirectional DSRC, which does not require line of sight to communicate.
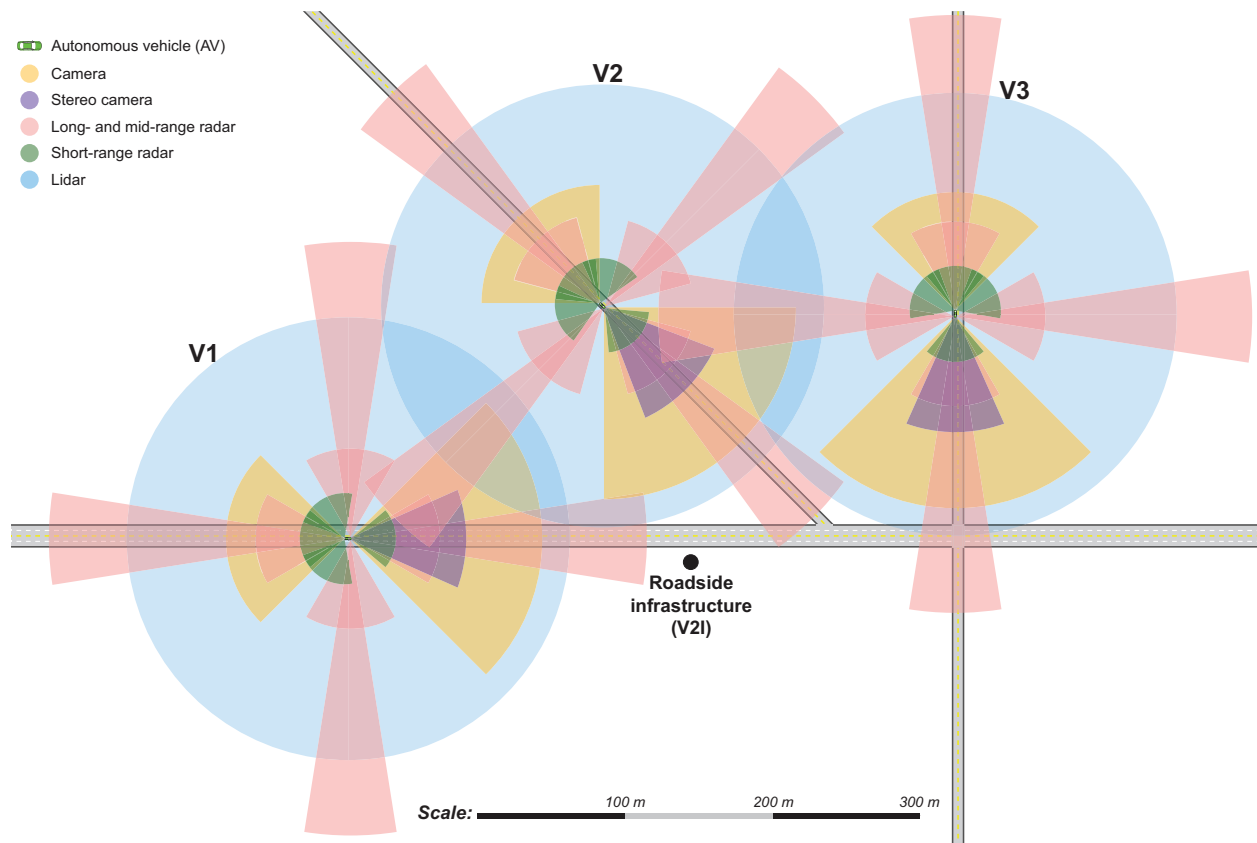
For gaps or limits in sensor coverage, Figure 8 illustrates the ability of several AVs to be in relatively close proximity to each other (less than 500 m line of sight from V1 to V3), yet still be potentially unaware of each other's presence. As impressive as the sensor coverage for the hypothetical AVs may appear to be (see Figure 4), each vehicle in Figure 8 is out of normal AV sensor range from one another. Not only would human-driven vehicles that are within 500 m line-of-sight separation (neglecting possible physical obstructions) likely be visible to each other, as illustrated in Figure 9, they would also be within normal DSRC range. (Roadside infrastructure equipment would also likely be within 500 m range in many traffic situations, as also illustrated in Figures 8 and 9.) With DSRC, they are able to not only (1) communicate and have a detailed awareness of each other (such as speed, heading, etc.) prior to entering the normal AV sensor range, but also (2) communicate beyond the DSRC range of individual vehicles (i.e., V1 can communicate with or be aware of V3 via V2 and/or the vehicle-to-infrastructure [V2I] roadside equipment). This communication permits the vehicles to maintain awareness of each other regardless of how well the AV sensors can see (or cannot see) the other vehicles (Moore, 2017; de Ponte Müller, 2017). However, AV sensing will still be critical for detection of any road user or roadway obstacle that is not part of the interconnected DSRC system (such as pets, wild animals, dropped cargo, downed trees, etc.).

Figure 8. Example illustration of the ability of several AVs to be in relatively close proximity to each other (less than 500 m line of sight from V1 to V3), yet still be out of normal AV sensor range and potentially unaware of each other's presence. (Sensor ranges are the same as those shown in Figure 4.)
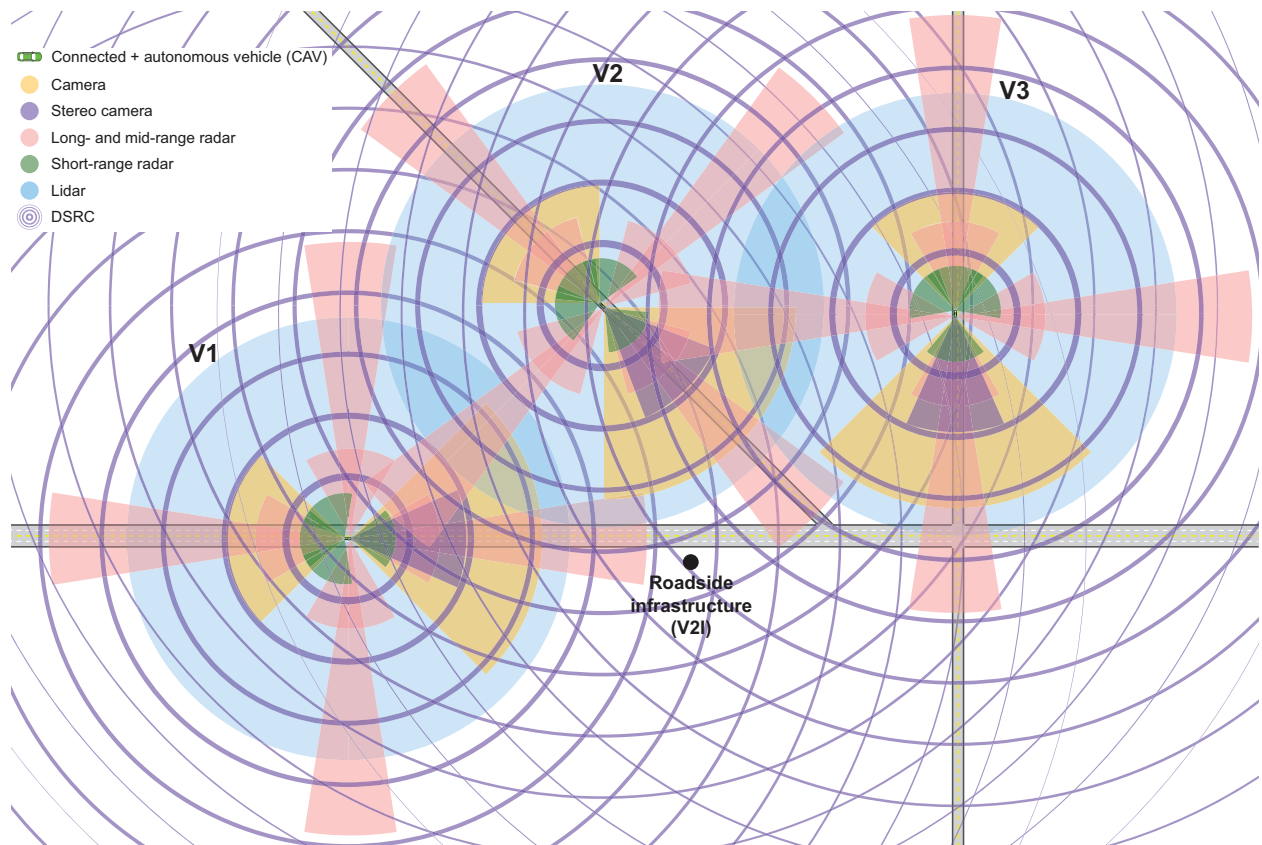
Figure 9. Example illustration of the overlapping DSRC ranges for each vehicle and the roadside infrastructure (V2I) equipment, allowing for detailed awareness of each vehicle (such as speed, heading, etc.) prior to entering the normal AV sensor ranges. (Sensor ranges are the same as those shown in Figure 4.)

Straight crossing path crashes

Other vehicles can travel through large blind spots or gaps in sensors, or potentially through zones where only one sensor is able to see the vehicle, or even skirt the edge of where two sensors overlap, creating a possible tracking problem as that vehicle repeatedly enters then leaves the field of view for a particular sensor. Each of these scenarios can result in minimal or possibly no coverage, or late coverage (in terms of safe reaction time). An example illustrating a similar overall layout and geometry to a documented Google AV crash that occurred on September 23, 2016, in Mountain View, California (California DMV, 2016) is shown in Figure 10. The exact geometry and speeds for the referenced crash are not identical to the simplified scenario shown here. Therefore, this discussion of an example crash scenario is not intended as an analysis of the specific referenced crash. However, the example scenario was selected because a similar scenario had proven to be problematic for a highly automated vehicle (level 3) in the real world. In the scenario illustrated here, two potential problems exist: the other vehicle is either (1) visible to only one sensor (i.e., lidar), or (2) it skirts the edge of a sensor's range (i.e., camera).

Assuming unobstructed line of sight for both human drivers and AV sensors, the other vehicle would have been visible to a human driver for the entire 7 s (or more) prior to a collision during both day or night (the approaching vehicle would be assumed to also have headlamps illuminated, negating the 75 m limit for nighttime vision). The other vehicle would have entered the range of the lidar sensor with just under 6 s to collision, possibly entering camera range around 5 s before collision (but possibly also remaining just outside of camera range).

With a human-driven vehicle needing a distance corresponding to just under 3 s of travel to stop at 65 km/h (40 mph), a human driver would have a buffer of 4 s (or more) to react and stop. (Stopping distances assume a dry road with a faster reaction time.) The AV needs a distance corresponding to just over 1.5 s of travel to stop at 65 km/h (40 mph), and would have a buffer of around 4 s (but not likely more) to react and stop during both day or night (most sensors are not affected by darkness or illumination levels). In this example scenario, the AV has approximately the same amount of time (or less) to respond as the human driver. Significant improvement in the time available for an AV to respond would require (1) increased sensor range, (2) increased sensor coverage, and/or (3) faster AV reaction time.
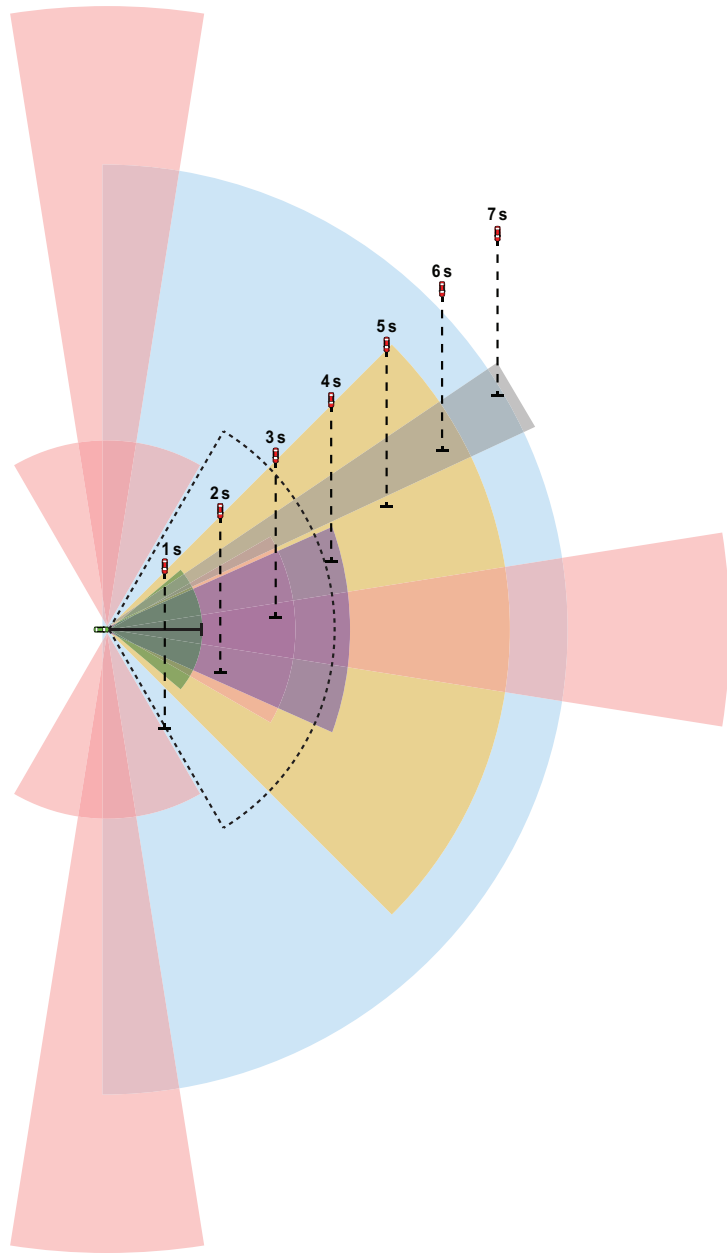
Figure 10. Straight crossing path crash scenario. (For clarity, only side and forward-facing AV sensors are shown here.)

Left turn across, opposite-direction crashes

Similar to the *straight crossing path* example, other vehicles can travel through zones where only one sensor is able to see the vehicle, or skirting the edge where two sensors overlap, creating a tracking problem as that vehicle enters then leaves the field of view in rapid succession for a particular sensor. The other vehicle might be seen as parallel, non-crossing traffic until very late (in terms of safe reaction time), prior to turning/crossing. An example illustrating a similar overall layout and geometry to the well-publicized Tesla crash that occurred on May 7, 2016, in Williston, Florida (NHTSA, 2017b) is shown in Figure 11. The exact geometry and speeds for the referenced crash are not identical to the simplified scenario shown here. Therefore, this discussion of an example crash scenario is not intended as an analysis of the specific referenced crash. However, the example scenario was selected because a similar scenario had proven to be problematic for a highly automated vehicle (level 2) in the real world. In the scenario illustrated here, the other vehicle (1) enters the sensor coverage area relatively late (less than 6 s to collision), and (2) skirts the edge of a sensor's range (i.e., long-range radar).

Assuming unobstructed line of sight for both human drivers and AV sensors, and assuming the other vehicle started to turn between 7 s and 6 s to collision, the other vehicle would have been visible to a human driver for the entire 7 s (or more) prior to a collision during both day or night (the approaching vehicle would be assumed to also have headlamps illuminated, negating the 75 m limit for nighttime vision). The other vehicle would have entered the range of the lidar sensor with just under 6 s to collision, then entered the coverage area of the camera and long-range radar at around 5 s, then stereo camera range at around 3 s, and short-range radar just before 2 s. (Detection that occurs after that time would be too late to stop the vehicle and avoid a collision.)

With a human-driven vehicle needing a distance corresponding to just over 3 s of travel to stop at 88 km/h (55 mph), a human driver would have a buffer of between 3 s and 4 s to react and stop. (Stopping distances assume a dry road with a faster reaction time.) The AV needs a distance corresponding to just over 2 s of travel to stop at 88 km/h (55 mph), and would have a buffer of around 4 s to react and stop during both day or night (most sensors are not affected by darkness or illumination levels). In this example scenario, the AV has approximately 1 s more than the human driver to respond. Significant improvement in the time available for an AV to

25

respond would require (1) increased sensor range, (2) increased sensor coverage, and/or (3) faster AV reaction time.
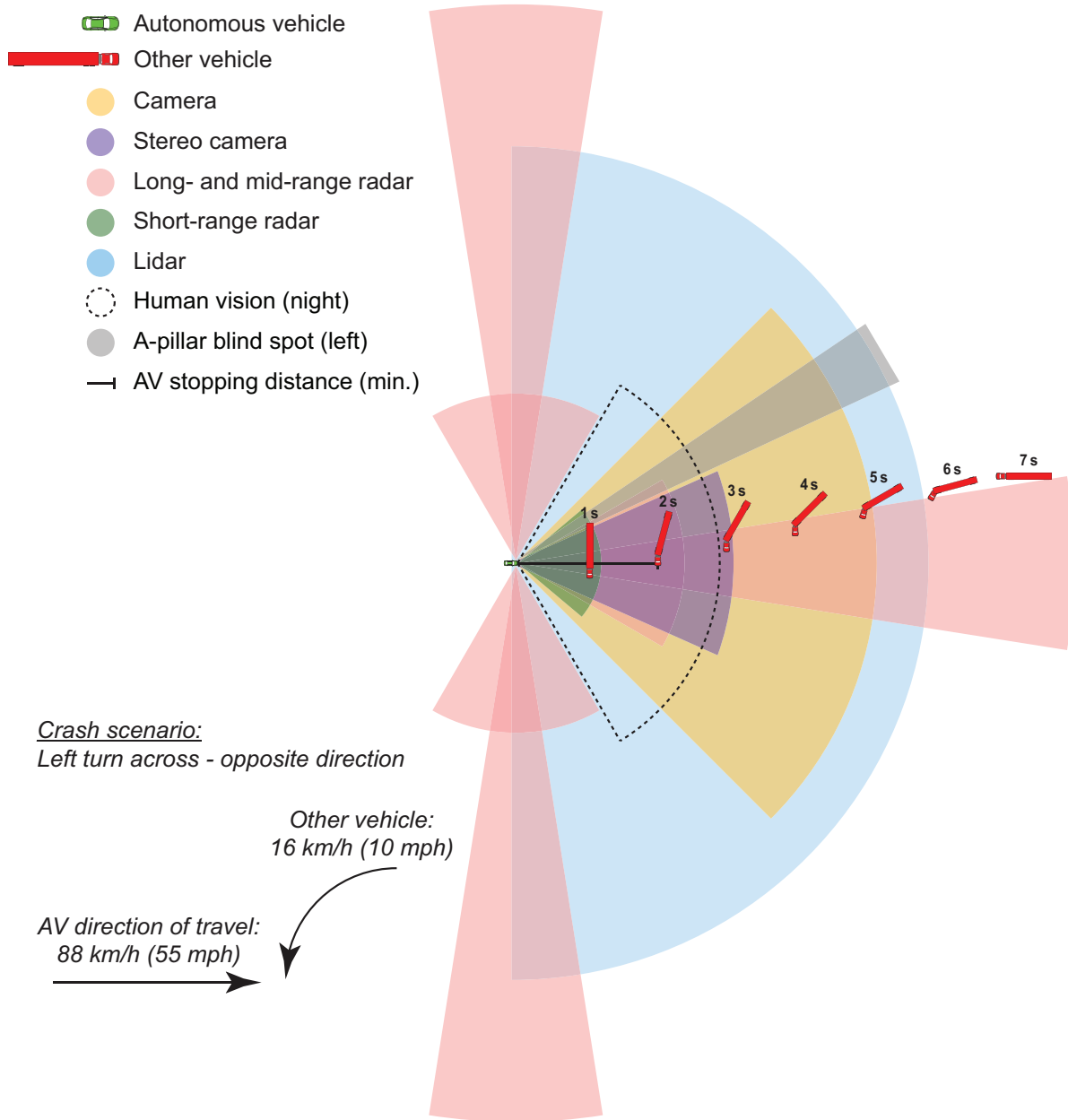

Figure 11. Left turn across, opposite-direction crash scenario. (For clarity, only side and forward-facing AV sensors are shown here.)

Sensor fusion

The selected case studies illustrated in this report show that some traffic scenarios still pose a challenge for automated vehicles. The two specific crash geometries described in the previous subsections (both considered angle-impact crashes) were also identified by NHTSA as being especially problematic for automated vehicles.[9] The likelihood or probability that an AV will react to a hazard (based on processing and perception) is a separate issue from theoretically available time to react (based on sensor range or technical capabilities). In a recent report investigating crash-imminent braking (CIB) systems (i.e., automated braking), NHTSA found that for four specific scenarios, including *straight crossing path* and *left turn across, opposite direction* crashes, "system performance, regardless of system configuration or settings, [was] not capable of reliably responding" (NHTSA, 2011a). In agreement with both crash scenarios presented in this report, the NHTSA report states that, "the limited time the target is in the field of view prior to impact challenges the system's ability to perform threat assessment and apply the CIB system. A target is usually recognized very late or not at all prior to impact" (NHTSA, 2011b). (These same findings were also quoted in the NHTSA investigative report for the Tesla crash referenced earlier in this report [NHTSA, 2017b].)[10]

However, such systems rely predominantly on radar and single cameras, and the potential to improve performance in these scenarios is considerably better when additional, complementary sensors such as lidar and stereo camera systems are all brought together to analyze the roadway and environment. This is particularly true when the sensor-fusion strategy of a system requires at least two sensors to agree before taking action (usually to avoid false activation) (Dickmann, et al., 2015). However, waiting for such sensor agreement can be problematic, especially when "complex or unusual shapes may delay or prevent the system from classifying certain vehicles as targets/threats" (NHTSA, 2017b). Ultimately, to maximize performance and available response time beyond the range of typical AV sensors, it is crucial to

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[9] It should be noted that these types of crashes are also problematic for human drivers, with 6,446 fatalities occurring in angle-impact crashes, contributing to around 18% of the 35,092 fatalities on U.S. roadways in 2015 (NHTSA, 2017a).

[10] While the CIB tests referenced by NHTSA were performed in 2011, no significant improvements in CIB performance for these types of crashes appear to have occurred since that report. The NHTSA (2017b) investigative report for the Tesla crash states that, "ODI surveyed a dozen automotive manufacturers and several major suppliers to determine if the AEB capabilities in crossing path collisions had changed since the CAMP CIB project was completed. None of the companies contacted by ODI indicated that AEB systems used in their products through MY 2016 production were designed to brake for crossing path collisions."

effectively fuse sensor input and data acquisition across all forms, integrating traditional AV technologies with connected-vehicle technologies (DSRC) for a complete CAV. If the vehicles in the previous crash examples were all connected vehicles (autonomous or human driven), they would have been well within DSRC range for the 7 s prior to a potential crash shown in each diagram. Implementation of omnidirectional DSRC satisfies the need for both (1) extended range and (2) extended coverage area identified in the two previous example crash scenarios.

Other useful sensors not discussed in this report

There are several other potentially useful sensors that might be considered for use with automated vehicles. The following list, though not exhaustive, identifies some of the most common additional sensors not discussed in this report, and their related capabilities:

- Far-infrared (heat; 50-1000 μm) sensor: Often used for night-vision systems for human drivers, far-infrared sensors are capable of passively detecting heat differences in the environment, which is particularly useful for detecting humans and animals present in the roadway.

- Mid- and near-infrared sensors: Capable of projecting and receiving middle (3-50 μm) and near (0.75-3 μm) infrared (IR) wavelengths, which allows these devices to illuminate their environment with an invisible (and potentially high power) IR source.

- Dead reckoning sensors and/or inertial measurement units (IMU): accelerometers, gyroscopes, and/or magnetometers in IMU; chassis control sensors in locations such as wheels, brakes, steering, etc. Used for both electronic stability-control systems and also potentially for vehicle navigation.

- Tire-based sensors: capable of detecting and communicating data about the current physical condition of each tire, specifications and manufacturing information, and/or current roadway conditions.

While the addition of the sensors listed here (or others) would extend the effectiveness of an AV's sensing capabilities, each additional sensor type would also add to the overall processing load for the self-driving system to properly interpret and respond to sensor inputs.

Key findings

This white paper analyzed and compared the sensing capabilities of human drivers and highly automated vehicles. The key findings from this study are as follows:

- Machines/computers are generally well suited to perform tasks like driving, especially in regard to reaction time (speed), power output and control, consistency (especially for tasks requiring constant vigilance), and multichannel information processing.

- At slow speeds, AV performance under degraded conditions may actually exceed human-driver performance under ideal conditions.

- Human drivers still generally maintain an advantage in terms of reasoning, perception, and sensing when driving.

- Matching (or exceeding) human sensing capabilities requires AVs to employ a variety of sensors, which in turn requires complete sensor fusion across the system, combining all sensor inputs to form a unified view of the surrounding roadway and environment.

- While no single sensor completely equals human sensing capabilities, some offer capabilities not possible for a human driver (e.g., accurate distance measurement with lidar, seeing through inclement weather with radar).

- Integration of connected-vehicle (CV) technology (e.g., DSRC) extends the effective range and coverage area of both human-driven vehicles and AVs, with a longer operating range and omnidirectional communication that does not require unobstructed line of sight the way human drivers and AVs generally do.

- Combining human-driven vehicles or AVs that can "see" traffic and their environment with CVs that can "talk" to other traffic and their environment maximizes potential awareness of other roadway users and roadway conditions.

- AV sensing will still be critical for detection of any road user or roadway obstacle that is not part of the interconnected DSRC system (such as pets, wild animals, dropped cargo, downed trees, etc.)

- A fully implemented connected autonomous vehicle (CAV) offers the best potential to effectively and safely replace the human driver when operating vehicles at automation levels 4 and 5.

References

AASHTO [American Association of State Highway and Transportation Officials]. (2001). *A policy on geometric design of highways and streets*. Available at: https://nacto.org/docs/usdg/geometric_design_highways_and_streets_aashto.pdf

Anthony, S. E. (2016, March 1). *The trollable self-driving car*. Available at: http://www.slate.com/articles/technology/future_tense/2016/03/google_self_driving_cars_lack_a_human_s_intuition_for_what_other_drivers.html

Audi. (2016). *Adaptive cruise control with stop & go function*. Available at: https://www.audi-technology-portal.de/en/electrics-electronics/driver-assistant-systems/adaptive-cruise-control-with-stop-go-function

Bhise, V. D. (2012). *Ergonomics in the automotive design process*. Boca Raton, FL: Taylor & Francis Group, LLC. Available at: https://doi.org/10.1201/b11237

Bosch. (2009). *Chassis systems control. LRR3: 3rd generation long-range radar sensor*. Available at: http://products.bosch-mobility-solutions.com/media/db_application/downloads/pdf/safety_1/en_4/lrr3_datenblatt_de_2009.pdf

Bosch. (2011). *Automotive handbook*. 8th ed., rev. and extended. Plochingen, Germany: Robert Bosch.

Boyce, P. R. (2014). *Human factors in lighting, third edition*. Boca Raton, FL: Taylor & Francis Group, LLC. Available at: https://doi.org/10.1201/b16707

Burress, B. (2007). *The unaided eye*. Available at: https://ww2.kqed.org/quest/2007/09/28/the-unaided-eye/

California DMV [California Department of Motor Vehicles]. (2016). *Report of traffic accident involving an autonomous vehicle (OL 316); Google September 23, 2016*. Available at: https://www.dmv.ca.gov/portal/wcm/connect/d3f31000-2d71-4483-9584-70be2f2ed2c5/google_092316.pdf?MOD=AJPERES

CAPTCHA [Completely Automated Public Turing test to tell Computers and Humans Apart]. (2017). *CAPTCHA: Telling humans and computers apart automatically*. Available at: http://www.captcha.net/

Continental. (2017). *Long range radar*. Available at: http://www.continental-automated-driving.com/Navigation/Enablers/Radar/Long-Range-Radar

Cummings, M. (2014). Man versus machine or man + machine? *IEEE Intelligent Systems, 29*(5), 62-69. Available at: http://ieeexplore.ieee.org/document/6949509/

CVEL [Clemson Vehicular Electronics Laboratory]. (2017). *Automotive electronic systems*. Available at: http://www.cvel.clemson.edu/auto/systems/auto-systems.html

Daimler. (2014). *World premiere for the traffic system of tomorrow – more efficient, safer, networked – and autonomous*. Available at: http://media.daimler.com/marsMediaSite/ko/en/9905075

Daimler. (2017a). *The auto pilot for trucks*. Available at: https://www.daimler.com/innovation/autonomous-driving/special/technology-trucks.html

Daimler. (2017b). *The Mercedes-Benz future bus*. Available at: https://www.daimler.com/innovation/autonomous-driving/future-bus.html

Dickmann, J., Appenrodt, N., Klappstein, J., Bloecher, H.-L., Muntzinger, M., Sailer, A., Hahn, M., & Brenk, C. (2015). Making Bertha see even more: Radar contribution. *IEEE Access, 3*, 1233-1247. Available at: http://ieeexplore.ieee.org/document/7161279/

Falson, A. (2014, November 19). *Mercedes-Benz steps up autonomous vehicle technology*. Available at: http://performancedrive.com.au/mercedes-benz-steps-autonomous-vehicle-technology-1913/

Fitts, P. M. (Ed.). (1951). *Human engineering for an effective air-navigation and traffic-control system*. Washington, D.C.: National Research Council.

Fitts, P. M. (1962). Functions of man in complex systems. *Aerospace Engineering, 21*, 34-39.

FMCSA [Federal Motor Carrier Safety Administration]. (2017). *Large truck and bus crash facts 2015*. Available at: https://www.fmcsa.dot.gov/safety/data-and-statistics/large-truck-and-bus-crash-facts-2015#A3

Ford. (2017). *Further with Ford*. Available at: https://media.ford.com/content/fordmedia/fna/us/en/news/2016/09/12/further-with-ford.html

Freedman, D. H. (2017). *Self-driving trucks*. Available at: https://www.technologyreview.com/s/603493/10-breakthrough-technologies-2017-self-driving-trucks/

Godsmark, P. (2017, February 24). *Driverless, autonomous, self-driving… naming a baby is easier than naming new car tech*. https://www.driverless.id/news/driverless-autonomous-self-driving-naming-baby-is-easier-than-naming-new-car-tech-0175495/

Google (2015). *Google self-driving car project monthly report, July 2015*. Available at: https://www.google.com/selfdrivingcar/files/reports/report-0715.pdf

Greibe, P. (2007). *Braking distance, friction and behaviour*. Available at: http://www.trafitec.dk/sites/default/files/publications/braking%20distance%20-%20friction%20and%20driver%20behaviour.pdf

Hammerschmidt, C. (2013, September 11). *Daimler, KIT send autonomous vehicle on historic course*. Available at: http://www.eenewsautomotive.com/news/daimler-kit-send-autonomous-vehicle-historic-course

Hyundai. (2016). *Hyundai motor company introduces new autonomous Ioniq concept at Automobility Los Angeles*. Available at: https://www.hyundaiusa.com/about-hyundai/news/corporate_hyundai-motor-company- introduces-new-autonomous-ioniq-concept-at-automobility-los-angeles4-20161116.aspx

Kenney, J. B. (2011). Dedicated short-range communications (DSRC) standards in the United States. *Proceedings of the IEEE, 99*(7), 1162-1182. Available at: http://ieeexplore.ieee.org/document/5888501/

Kent, L. (2015). *Autonomous cars can only understand the real world through a map*. Available at: http://360.here.com/2015/04/16/autonomous-cars-can-understand-real-world-map/

Krok, A. (2016, November 16). *Hyundai's next Ioniq is a fully autonomous concept*. Available at: https://www.cnet.com/roadshow/news/hyundais-next-ioniq-is-a-fully-autonomous-concept/

LeddarTech. (2016). *LeddarTech launches LeddarVu, a new scalable platform towards high-resolution LiDAR*. Available at: http://leddartech.com/leddartech-launches-leddarvu-new-scalable-platform-towards-high-resolution-lidar/

Lee, S. & Lim, A. (2013). An empirical study on ad hoc performance of DSRC and Wi-Fi vehicular communications. *International Journal of Distributed Sensor Networks, 9*(11). Available at: http://journals.sagepub.com/doi/full/10.1155/2013/482695

Lee, Y. M. & Sheppard, E. (2016). The effect of motion and signalling on drivers' ability to predict intentions of other road users. *Accident Analysis and Prevention, 95*, 202-208. Available at: http://www.sciencedirect.com/science/article/pii/S0001457516302408

MacAdam, C. C. (2003). Understanding and modeling the human driver. *Vehicle System Dynamics, 40*(1-3), 101-134. Available at: http://hdl.handle.net/2027.42/65021

McDonald, M. (2015, October 16). *Automotive fusion: Combining legacy and emerging sensors for safer and increasingly autonomous vehicles*. Available at: http://www.sensorsmag.com/components/automotive-fusion-combining-legacy-and-emerging-sensors-for-safer-and-increasingly

Mercedes-Benz. (2017). *Distronic Plus*. Available at: https://www.mbusa.com/mercedes/technology/videos/detail/class-CLA_Class/title-claclass/videoId-caf758b451127410VgnVCM100000ccec1e35RCRD

Moore, N. C. (2017, June 23). *Mcity demos: Self-driving cars can be even safer with connected technology*. Available at: http://ns.umich.edu/new/multimedia/videos/24932-mcity-demos-self-driving-cars-can-be-even-safer-with-connected-technology

NHTSA [National Highway Traffic Safety Administration]. (2016). *Federal automated vehicles policy*. Available at: https://one.nhtsa.gov/nhtsa/av/pdf/Federal_Automated_Vehicles_Policy.pdf

NHTSA [National Highway Traffic Safety Administration]. (2017a). *Fatality Analysis Reporting System (FARS) encyclopedia*. Available at: http://www-fars.nhtsa.dot.gov/Main/index.aspx

NHTSA [National Highway Traffic Safety Administration]. (2017b). *ODI resume. Automatic vehicle control systems*. Available at: https://static.nhtsa.gov/odi/inv/2016/INCLA-PE16007-7876.PDF

NHTSA [National Highway Traffic Safety Administration]. (2017c). *Vehicle-to-vehicle communications*. Available at: https://www.safercar.gov/v2v/index.html

NSC [National Safety Council]. (2017). *The most dangerous time to drive*. Available at: http://www.nsc.org/learn/safety-knowledge/Pages/news-and-resources-driving-at-night.aspx

Ohnsman, A. (2017, May 14). *Waymo forges driverless car tech tie-up with Lyft amid its legal battle with Uber*. Available at: https://www.forbes.com/sites/alanohnsman/2017/05/14/waymo-forges-driverless-car-tech-tie-up-with-lyft-amid-its-legal-battle-with-uber/#4486bc126594

Olson, P. L. & Sivak, M. (1986). Perception-response time to unexpected roadway hazards. *Human Factors, 28*(1), 91-96. Available at: http://journals.sagepub.com/doi/abs/10.1177/001872088602800110

Owsley, C. & McGwin, G., Jr. (2010). Vision and driving. *Vision Research, 50*(23), 2348-2361.

Pleskot, K. (2016, November 16). *Hyundai Ioniq autonomous concept debuts hidden lidar system in L.A.* Available at: http://www.motortrend.com/news/hyundai-ioniq-autonomous-concept-debuts-hidden-lidar-system-in-l-a/

de Ponte Müller, F. (2017). Survey on ranging sensors and cooperative techniques for relative positioning of vehicles. *Sensors, 17*, 271-287. Available at: http://www.mdpi.com/1424-8220/17/2/271

Popa, B. (2012, July 28). *Gentlemen's agreement: Not so fast, sir!* Available at: https://www.autoevolution.com/news/gentlemens-agreement-not-so-fast-sir-47736.html

Quanergy. (2015). *360° 3D LIDAR M8-1 sensor*. Available at: http://www.lidarusa.com/uploads/5/4/1/5/54154851/quanergy_m8-1_lidar_datasheet_v4.0.pdf

RITA [Research and Innovative Technology Administration]. (2016). *Dedicated short-range communications (DSRC)*. Available at: https://www.its.dot.gov/factsheets/pdf/JPO-034_DSRC.pdf

Rosenholtz, R., Li, Y., & Nakano, L. (2007). Measuring visual clutter. *Journal of Vision, 7*(2), 1-22. Available at: http://jov.arvojournals.org/article.aspx?articleid=2122001

Schoettle, B. & Flannagan, M. J. (2011). *A market-weighted description of low-beam and high-beam headlighting patterns in the U.S.: 2011* (Technical Report No. UMTRI-2011-33). Ann Arbor: University of Michigan Transportation Research Institute.

Sivak, M. & Schoettle, B. (2015). *Road safety with self-driving vehicles: General limitations and road sharing with conventional vehicles* (Technical Report No. UMTRI-2015-2). Available at: http://hdl.handle.net/2027.42/111735

Sivak, M., Schoettle, B., Reed, M. P., & Flannagan, M. J. (2007). Body-pillar vision obstructions and lane-change crashes. *Journal of Safety Research, 38*, 557-561. Available at: http://www.sciencedirect.com/science/article/pii/S002243750700103X

Sommer, C., Eckhoff, D., & Dressler, F. (2013). IVC in cities: Signal attenuation by buildings and how parked cars can improve the situation. *IEEE Transactions on Mobile Computing, 13*(8), 1733-1745. Available at: http://ieeexplore.ieee.org/document/6544519/

Texas DOT [Texas Department of Transportation]. (2017). *Setting speed limits*. Available at: http://www.txdot.gov/driver/laws/speed-limits/setting.html

Utah DOT [Utah Department of Transportation]. (2013). *Utah DOT leveraging LiDAR for asset management leap*. Available at: http://blog.udot.utah.gov/2013/02/utah-dot-leveraging-lidar-for-asset-management-leap/

Walker, A. (2015, October 12). *5 cities with driverless public buses on the streets right now*. Available at: http://gizmodo.com/5-cities-with-driverless-public-buses-on-the-streets-ri-1736146699

de Winter, J. C. F. & Dodou, D. (2014). Why the Fitts list has persisted throughout the history of function allocation. *Cognition, Technology & Work, 16*(1), 1-11. Available at: https://link.springer.com/article/10.1007/s10111-011-0188-1

WCP [Woodside Capital Partners]. (2016). *Beyond the headlights: ADAS and autonomous sensing*. Available at: http://www.woodsidecap.com/wcp-publishes-adasautonomous-sensing-industry-beyond-headlights-report/

Appendix

The equations corresponding to each minimum-stopping-distance calculation are shown below:

$$Reaction\ time\ distance = reaction\ time \times speed \tag{1}$$

$$Braking\ distance_{min} = \frac{v^2}{2\mu g} = \frac{speed^2}{2 \times (friction\ coefficient) \times (gravitational\ acceleration)} \tag{2}$$

$$Stopping\ distance_{min} = reaction\ time\ distance + braking\ distance_{min} \tag{3}$$

An example set of calculations for a vehicle traveling at 80 km/h (22.22 m/s or 50 mph) on a dry roadway (μ = 0.8) with a reasonably fast human-driver reaction time (1.6 s) is shown below:

$$Reaction\ time\ distance = 1.6\ s \times 22.22\ m/s = 35.55\ m$$

$$Braking\ distance_{min} = \frac{(22.22\ m/s)^2}{2 \times (0.8) \times (9.81\ m/s^2)} = 31.46\ m$$

$$Stopping\ distance_{min} = 35.55\ m + 31.46\ m = 67.01\ m$$

Results for all four scenarios and for speeds (35 km/h to 240 km/h) are shown in Figures A1 through A6.
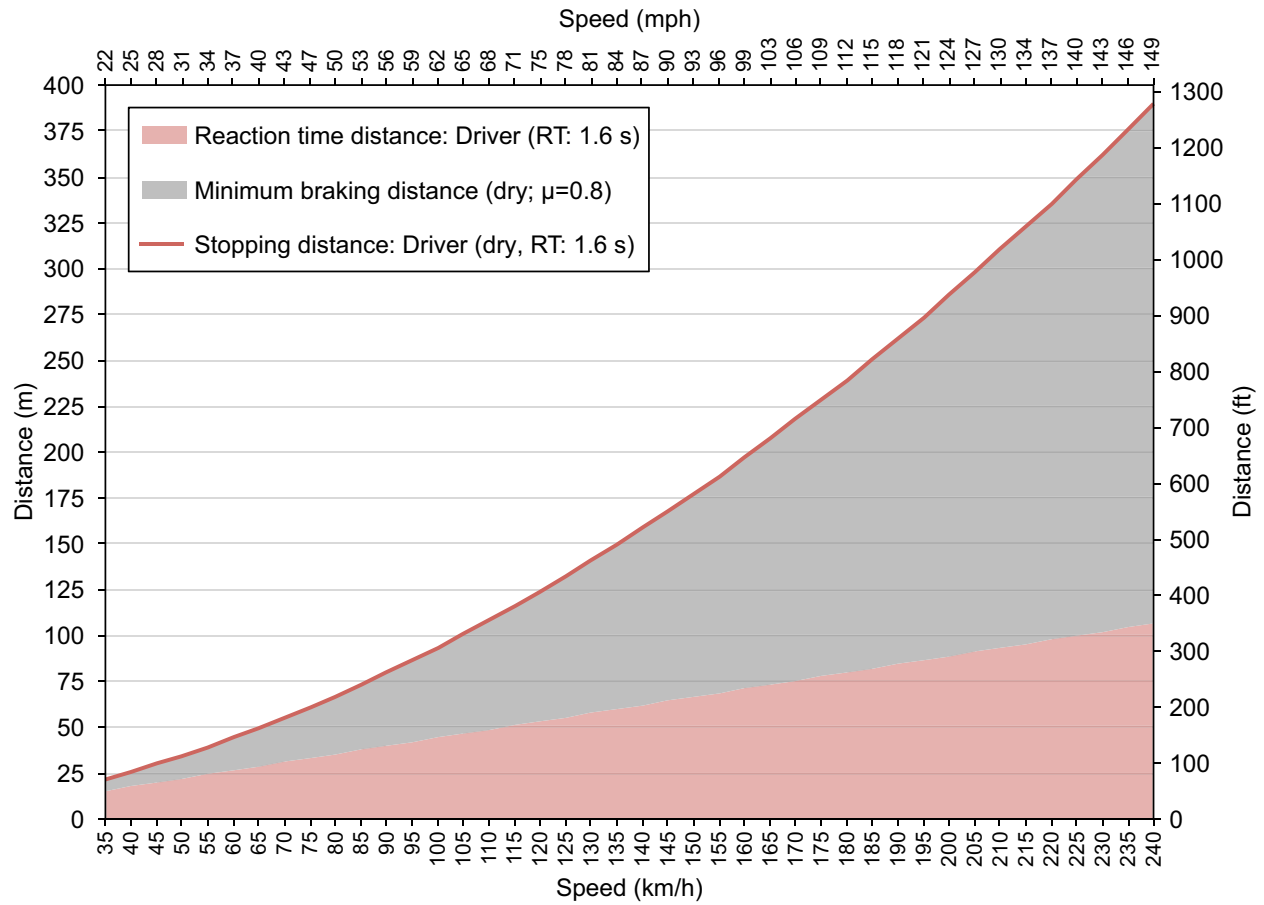
Figure A1. Calculated minimum stopping distance (red line) for a human driver under ideal conditions (dry roadway with a faster reaction time). Minimum stopping distance is the sum of driver reaction-time distance (red shading) and minimum braking distance for the roadway conditions (gray shading).
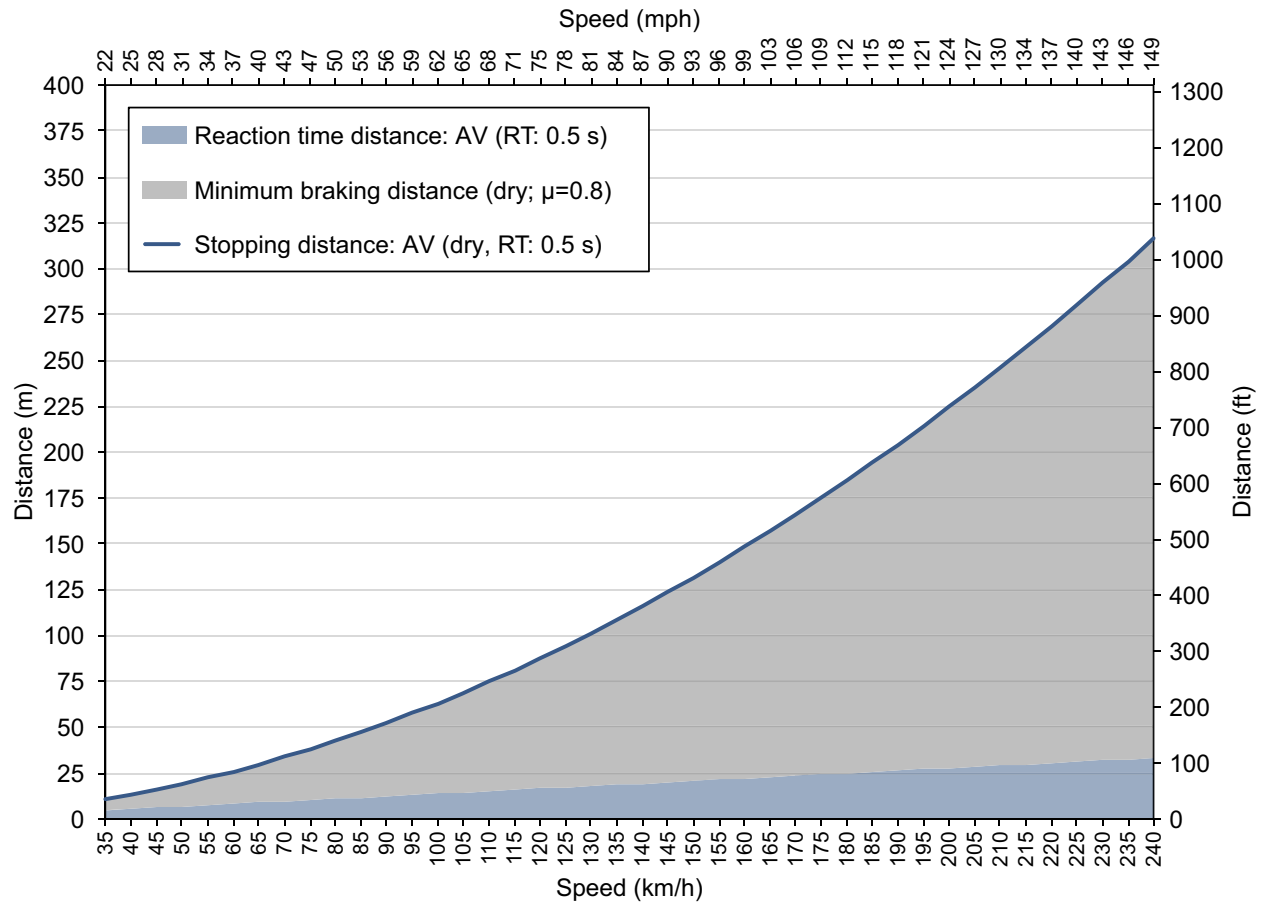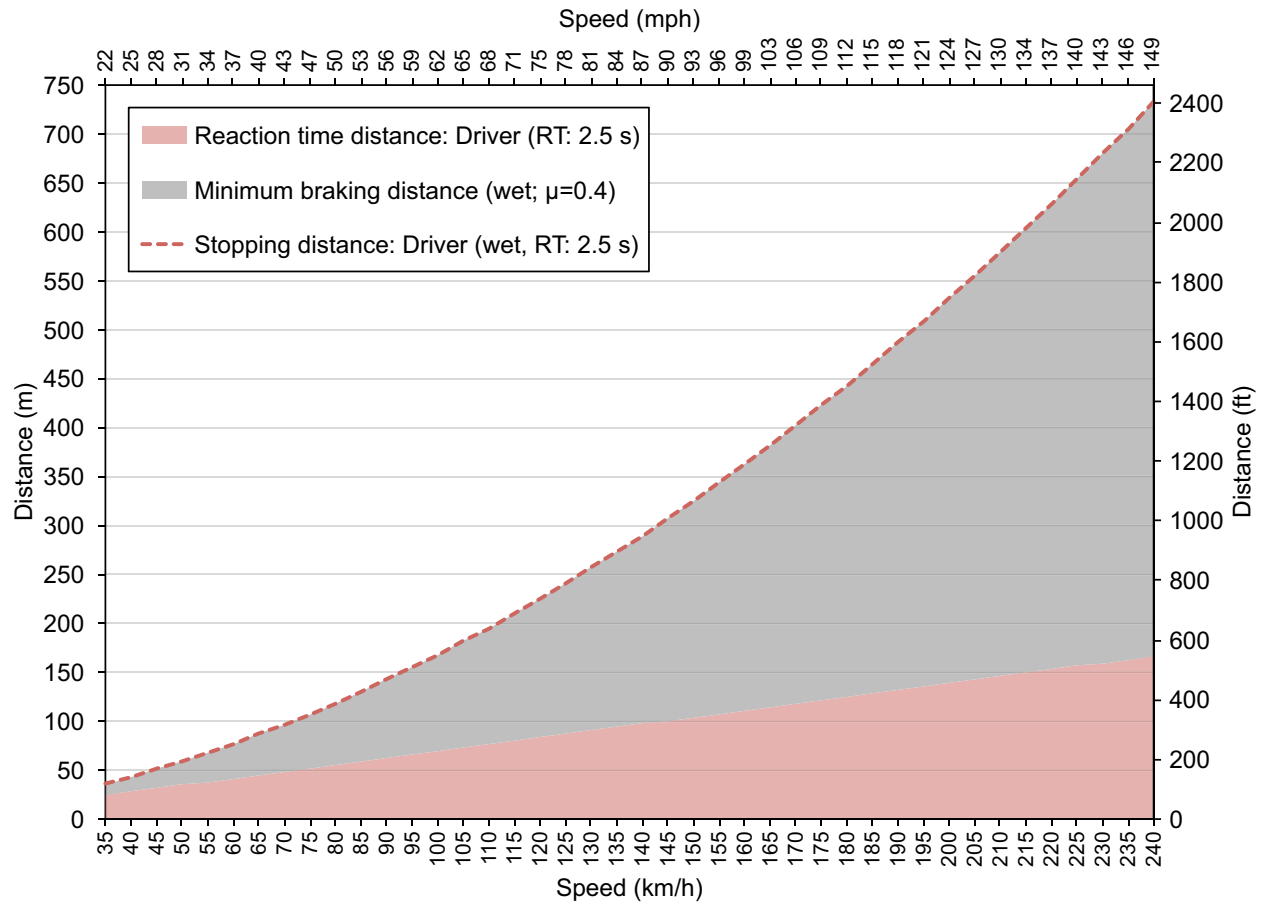
Figure A2. Calculated minimum stopping distance (blue line) for an automated vehicle (AV) under ideal conditions (dry roadway with a faster reaction time). Minimum stopping distance is the sum of driver reaction-time distance (blue shading) and minimum braking distance for the roadway conditions (gray shading).

Figure A3. Calculated minimum stopping distance (red dashed line) for a human driver under degraded conditions (wet roadway with a slower reaction time). Minimum stopping distance is the sum of driver reaction-time distance (red shading) and minimum braking distance for the roadway conditions (gray shading).
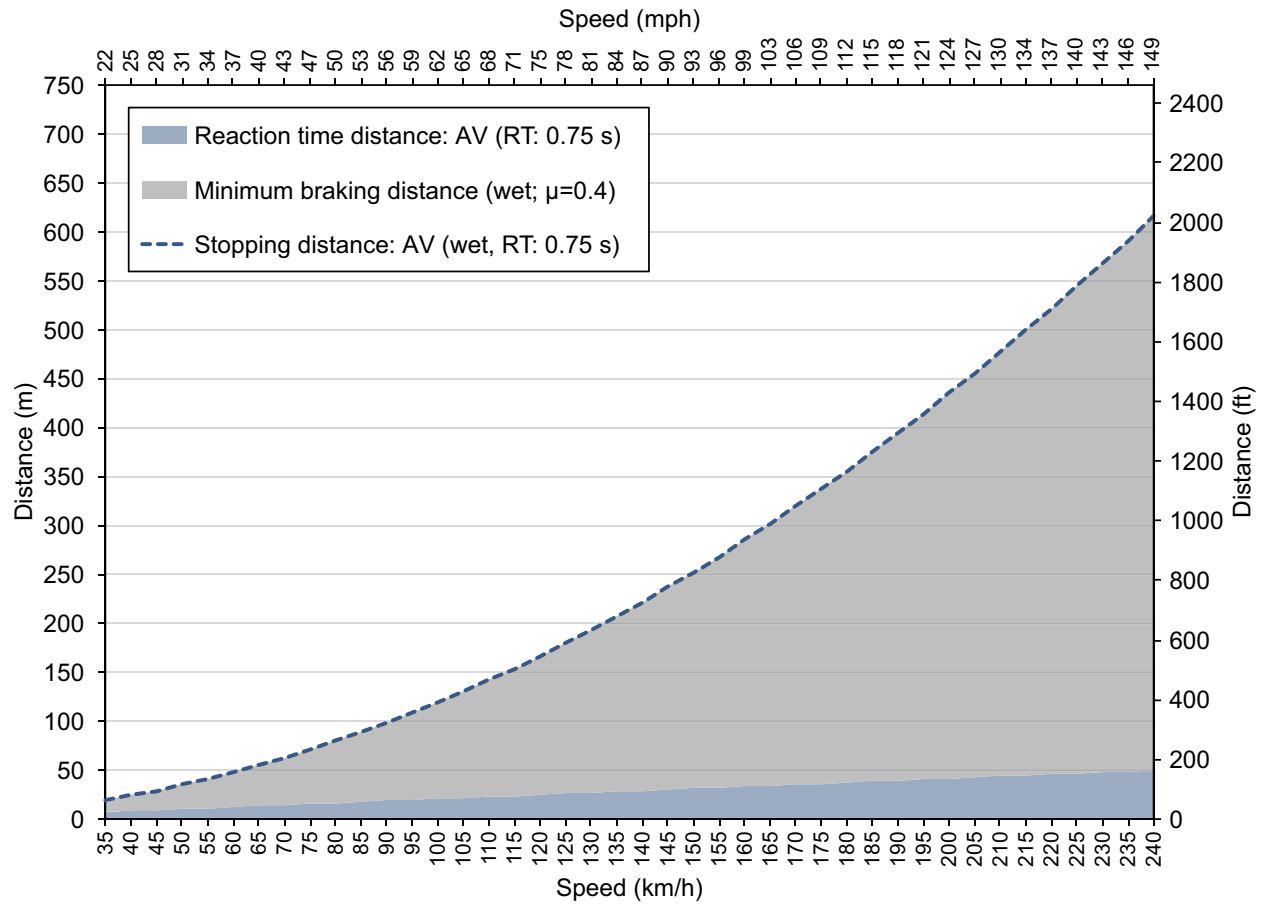
Figure A4. Calculated minimum stopping distance (blue dashed line) for an automated vehicle (AV) under degraded conditions (wet roadway with a slower reaction time). Minimum stopping distance is the sum of driver reaction-time distance (blue shading) and minimum braking distance for the roadway conditions (gray shading).
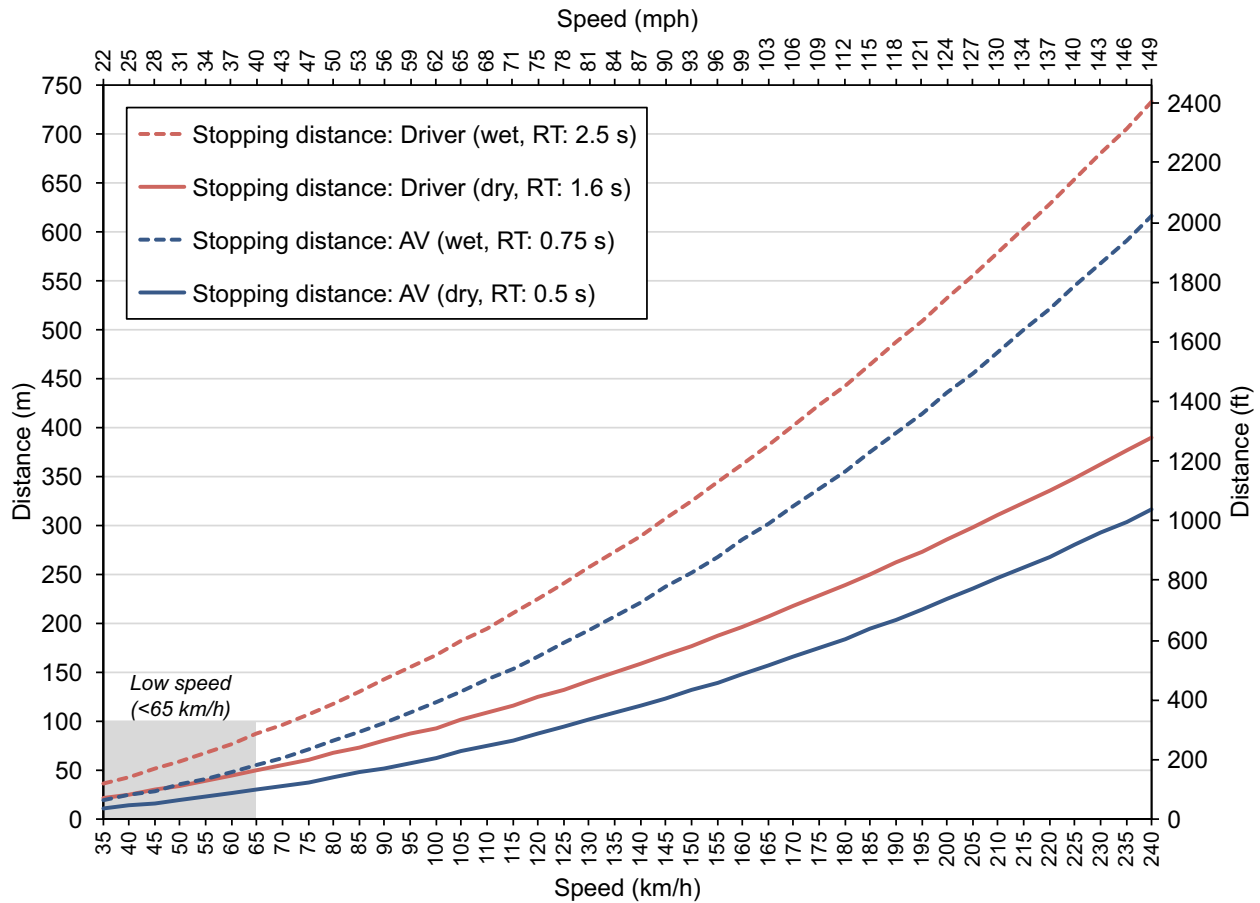
Figure A5. Summary of calculated minimum stopping distances for human drivers and an automated vehicle (AV) under ideal conditions (dry roadway with faster reaction time) and degraded conditions (wet roadway with a slower reaction time). For a more detailed examination of the gray-shaded area corresponding to performance at lower speeds (< 65 km/h), see Figure A6.
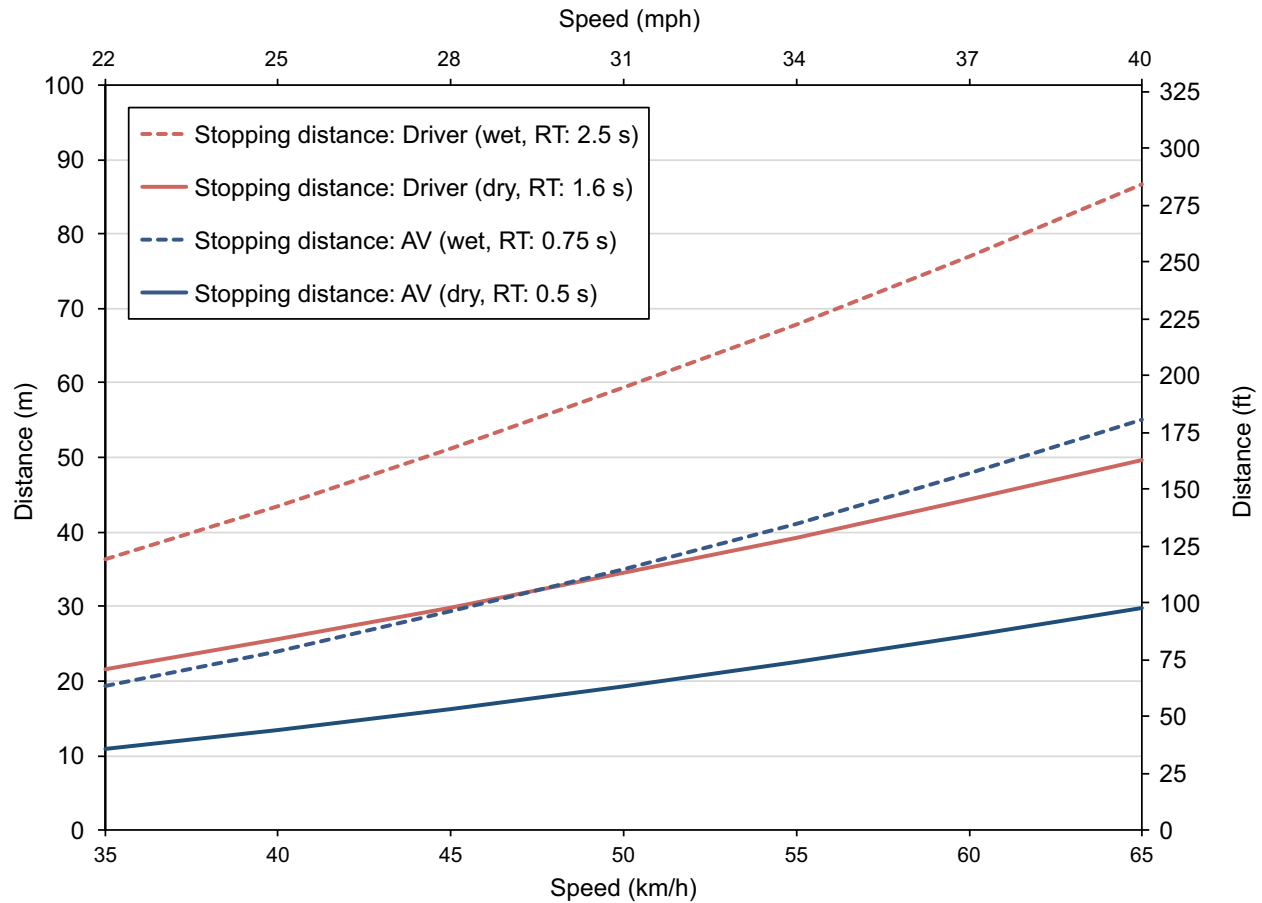
Figure A6. Summary of calculated minimum stopping distances for human drivers and an automated vehicle (AV) under ideal conditions (dry roadway with faster reaction time) and degraded conditions (wet roadway with a slower reaction time) at lower speeds (35 km/h to 65 km/h). For speeds under 50 km/h (31 mph), calculations of AV stopping performance under degraded conditions (dashed blue line) surpass human-driver stopping performance under ideal conditions (solid red line).