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Review

Autonomous vehicle perception: The technology of today and tomorrow

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ABSTRACT

Perception system design is a vital step in the development of an autonomous vehicle (AV). With the vast selection of available off-the-shelf schemes and seemingly endless options of sensor systems implemented in research and commercial vehicles, it can be difficult to identify the optimal system for one's AV application. This article presents a comprehensive review of the state-of-the-art AV perception technology available today. It provides up-to-date information about the advantages, disadvantages, limits, and ideal applications of specific AV sensors; the most prevalent sensors in current research and commercial AVs; autonomous features currently on the market; and localization and mapping methods currently implemented in AV research. This information is useful for newcomers to the AV field to gain a greater understanding of the current AV solution landscape and to guide experienced researchers towards research areas requiring further development. Furthermore, this paper highlights future research areas and draws conclusions about the most effective methods for AV perception and its effect on localization and mapping. Topics discussed in the Perception and Automotive Sensors section focus on the sensors themselves, whereas topics discussed in the Localization and Mapping section focus on how the vehicle perceives where it is on the road, providing context for the use of the automotive sensors. By improving on current state-of-the-art perception systems, AVs will become more robust, reliable, safe, and accessible, ultimately providing greater efficiency, mobility, and safety benefits to the public.

1. Introduction

Autonomous vehicle (AV) technology is making a prominent appearance in our society in the form of advanced driver assistance systems (ADAS) in both research and commercial vehicles. These technologies aim to reduce the amount and severity of accidents, increase mobility for people with disabilities and the elderly, reduce emissions, and use infrastructure more efficiently (Fagnant and Kockelman, 2015). One of the major motivations accelerating the advancement of AV technologies is their insusceptibility to human-related errors, such as distraction, fatigue, and emotional driving, which currently cause approximately 94% of accidents according to a statistical survey completed by the National Highway Traffic Safety Administration (NHTSA) (Singh, 2015).

As research, testing, and deployment of vehicles with AV technology is escalating around the world, the development of standardized guidelines and regulations has become a major focus to ensure safe integration into society. The U.S. Department of

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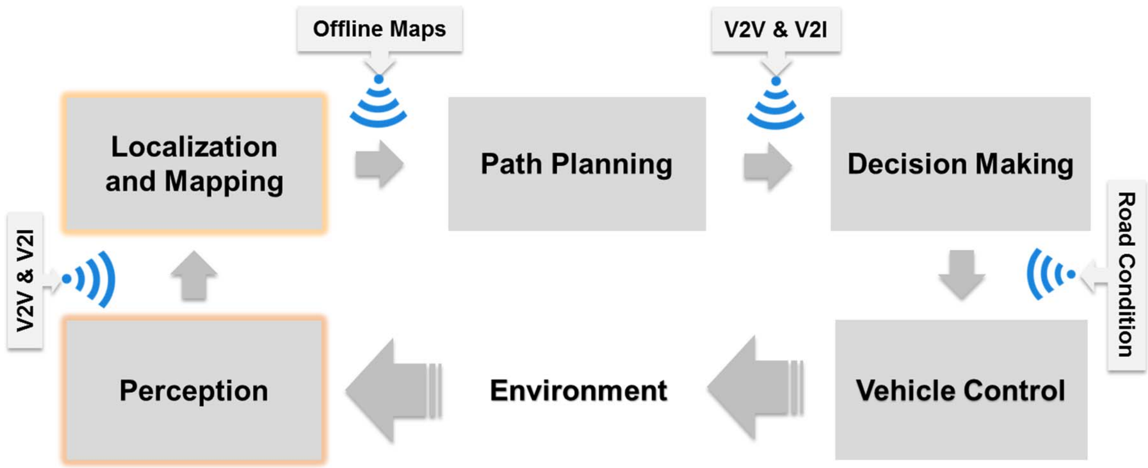

Fig. 1. Overview of the autonomous navigation process.

Transportation and the NHTSA have recently adopted the Society of Automotive Engineers international standard for automation levels which define autonomous vehicles from Level 0 (the human driver has full control) to Level 5 (the vehicle completely drives itself) (Transportation, 2016). Currently, due to limitations and high costs of available sensors, most commercial vehicles only include Level 1 to Level 2 autonomy, which require constant driver attention and control. The autonomous features in these vehicles generally consist of emergency braking, blind spot detection, and/or lane keeping. Nonetheless, Level 3 autonomous features are available in the Tesla Model S and Model X. However, recent accidents have initiated concerns regarding the drivers' understanding and capability of using the technology safely (Krisher and Durbin, 2016).

Presently, a major concern is the occurrence of new, unsafe driving practices as a result of drivers who do not understand or are not aware of how the AV technologies work (Kyriakidis et al., 2017; Lu et al., 2016). Furthermore, in order for autonomous features and vehicles to have significant, far-reaching effects in improving safety, mobility and efficiency, the public must understand the capabilities of the technology (Kyriakidis et al., 2015, 2017; Lu et al., 2016). This includes important factors such as the limitations of the technology, the application for the technology, and the appropriate scenarios to use and/or rely on the technology.

As a brief overview, autonomous vehicle navigation can be visualized as five main components (Fig. 1): Perception, Localization and Mapping, Path Planning, Decision Making, and Vehicle Control (Cheng, 2011). Perception uses sensors to continuously scan and monitor the environment, similar to human vision and other senses (Maurer et al., 2016). Localization and mapping algorithms calculate the global and local location of the ego-vehicle and map the environment from sensor data and other perception outputs (Maurer et al., 2016). Path planning determines possible safe routes for the ego-vehicle based on perception, and localization and mapping information (Katrakazas et al., 2015). The decision-making component is responsible for calculating the optimal route based on the possible paths, the current vehicle state, and the environment information (e.g., road attributes, weather conditions, road signs, etc.) (Maurer et al., 2016). The vehicle control module will then calculate the appropriate vehicle command (torque, acceleration, steering wheel angle, etc.) in order to follow the optimal route decision, such as a lane change, a right turn, or another maneuver (Gruyer et al., 2016b). It is important to note that the autonomous navigation process is a high frequency recursive process. This allows AVs to effectively handle high-speed motion and dynamic objects, such as pedestrians, motorcycles, and cars (Julier and Durrant-Whyte, 2003). An overview of the autonomous navigation process is shown in Fig. 1. This paper will focus on the "Perception" and "Localization and Mapping" stages.

This paper aims to provide a comprehensive review of the state-of-the-art AV perception technology to address a lack of synthesized information about sensor, hardware, and algorithm requirements for effective AV perception. In general, robust and reliable perception, and localization and mapping are required in order to make accurate and reliable decisions for vehicle control. This paper provides a review of the current sensor technology used for perception, as well as an overview of the methods used for localization and mapping.

In essence, this paper aims to answer the following questions:

- Which sensors are currently used in prominent research and commercial vehicles?
- What are the current advantages and shortcomings of the sensors?
- Which localization and mapping techniques are being used in research and commercial vehicles with respect to sensing the ego-vehicle's environment?
- What are the shortcomings of these localization and mapping methods and how can they be improved?
- What are the current areas of research that need to be addressed?
- How will this technology evolve in the future?

The paper is organized as follows. Section 2 introduces the background of AV research. Section 3 discusses the capabilities and shortcomings of automotive sensors commonly used in research and commercial vehicles. Section 4 provides an overview of localization and mapping techniques. Section 5 discusses the future of research in AV perception, providing useful insight for experienced AV researchers and engineers, and Section 6 concludes the review paper. Note that, although obstacle detection and tracking, road detection and tracking, ego-localization, and environment estimation are subcomponents of AV perception, these topics are considered outside of the scope of this paper and will not be discussed in detail. Further information about these topics may be found in Zhu et al. (2017).

It is worth to note that this paper's Localization and Mapping section was included to provide the context for how the ego-vehicle senses its surroundings and to illustrate how perception and sensing are closely related to localization and mapping. For example, an AV must know where it is on the road (through localization) to better estimate which objects are in its surroundings. A more practical example might be if an AV has sensed (through localization and mapping) that it is nearing a crosswalk, the vehicle should prioritize sensing for pedestrians around the crosswalk (which can only be done if the vehicle has localized itself). The link between perception and sensing, and localization and mapping works in the opposite direction as well. For example, if a vehicle senses road markings to the left and right of the vehicle, then the vehicle is likely to be in the center of the road, and thus, localization algorithms should be updated accordingly. Furthermore, the sensor technology (e.g., GPS, IMU, LIDAR, etc.) discussed in the Perception and Automotive Sensing section informs how localization and mapping algorithms are implemented, as discussed in the Localization and Mapping section.

Finally, note that the purpose of this paper is to provide an overview of current AV perception research and to identify areas of AV perception that require further work. This paper is meant to be used as a guide for future research, as well as provide essential information about perception for newcomers to the AV field. Thus, detailed analyses or rankings of perception algorithms and current sensors (which change regularly with the rapid advancement of research in this field) are outside of the scope of this paper. Nonetheless, the reader is strongly encouraged to investigate such analyses further.

This article can also benefit researchers through providing tables and figures that synthesize AV research in the following areas:

- Table 1: challenges in AV research and the extent to which the challenges have been addressed
- Table 2: advantages and disadvantages of common passive and active sensors
- Table 3: sensor arrangements in prominent research and commercial vehicles
- Table 4: autonomous features available in commercial vehicles
- Table 5: localization and mapping methods used by prominent research vehicles
- Fig. 1, 4 and 5: various autonomous navigation processes
- Figs. 2 and 3: AV history and milestones

Researchers may refer to these figures and tables when developing presentations, deciding on future research areas, choosing AV sensors, or developing new autonomous features.

2. History and background information

Since before the twenty-first century, researchers and industrial leaders have been competing to develop the first fully autonomous vehicle that is robust, reliable and safe enough for real-world and high-speed driving environments. Major contributors to early AV research can be attributed to AV tests and competitions held around the world. These competitions provided opportunities for industry and researchers to assess the capabilities and boundaries of AVs in various driving environments. However, more importantly, they identified major difficulties and shortcomings in AV software and hardware, some of which remain unresolved today.

One of the first long-distance AV road tests, "No Hands Across America," was introduced in 1995 (Bertozzi et al., 2000; Jochem and Pomerleau, 1995). This event pushed the boundaries of AV technology requiring the AV to steer across the United States while the human drivers controlled the vehicle' s acceleration and braking. Around the same time, an AV drove from Germany to Denmark in the "Munich to Odense UBM Test" (Bertozzi et al., 2000; Maurer et al., 1996). In 1998, an AV journeyed through the rolling hills and unpredictable weather conditions of Italy in the "ARGO Project" (Bertozzi et al., 1998, 2000; Broggi et al., 2000). In each of these tests, the AVs drove autonomously for 90–98% of the journey using primitive lane departure warning systems, lane keeping systems, and inter-distance/speed regulation systems (Bertozzi et al., 1998).

Moreover, through these tests, vehicle developers noted many areas in AV technology requiring significant improvement. These areas included image processing and other perception techniques; driving in complex, urban scenarios and poor weather conditions; and improving erroneous obstacle and road marking detection (Behringer and Maurer, 1996; Bertozzi et al., 1998, 2000). For example, ARGO' s lane detection algorithm required ideal road conditions in order to drive autonomously, including flat and weakly curved (or straight) roads, and roads with excellent road markings (Broggi et al., 2000). Thus, much of the difficulty and unpredictability of real-world autonomous driving was eliminated in this test. Furthermore, in both "No Hands Across America" and "Munich to Odense UBM Test," the AVs struggled to drive in unfavorable lighting conditions, such as dark tunnels, or when sunlight pointed directly in the camera lens (Bertozzi et al., 2000). The difficulties encountered related to lighting conditions have begun to be addressed with the improved vision technology and algorithms (such as using the HSL instead of RGB color space), the fusion of two camera data streams, and the fusion of active and passive sensors (Cacciola, 2007; Chan et al., 2007). However, work still needs to be completed in this area and will be further discussed in Section 3.

In 2003, the next major competition was initiated by the Defense Advanced Research Projects Agency (DARPA) which required vehicles to drive without the aid of road markings through an off-road desert course (Rouff and Hinchey, 2011). The first DARPA

Table 1
Summary of Problems Exposed and Addressed by AV Projects.

Project(s)/Competition(s)	Problems exposed/addressed by project	Current state of problem: Largely addressed (LA), relatively addressed (RA) or largely unaddressed (UA)
PROMETHEUS (1987–1995) (Oagana, 2016; Eureka, 1995; Amin et al., 1995; Eleter and Rombaut, 1996)	• Autonomous lane keeping • Adaptive cruise control • Automatic emergency calling systems	• LA • LA • LA
No Hands Across America (1995), Munich to Odense UBM Test (1995), ARGO(1998) (Bertozzi et al., 2000; Jochem and Pomerleau, 1995; Maurer et al., 1996; Bertozzi et al., 2000; Broggi et al., 2000; Behringer and Maurer, 1996)	• Vision-based object detection/tracking • Perception in unfavorable lighting conditions • Improvement of obstacle and road marking detection • Complexities of urban driving • Perception in difficult weather conditions	• LA • RA • RA • UA • UA
DARPA Grand Challenge (2004), Second DARPA Grand Challenge (2006), (Rouff and Hinchey, 2011; Walton, 2004; Buehler et al., 2007)	• Off-road navigation • Obstacle avoidance	• LA • RA
DARPA Urban Challenge(2007) (Rouff and Hinchey, 2011; Campbell et al., 2010; Buehler et al., 2009; Montemerlo et al., 2008)	• Traffic light and sign detection • Ability to test in real traffic situations • Obstacle detection - especially pedestrian and cyclist detection • High-speed autonomous driving; efficiency of detection algorithms • Complex urban driving (dense traffic, intersections, etc.)	• LA • RA • RA • RA • UA
Highly Automated Vehicles for Intelligent Transportation (HAVEit) (2008–2011) (HAVEit, 2008; Vanholme et al., 2013)	• Temporary autonomous driving systems • V2V to increase redundancy in data • Safety software architecture of AVs; detection of hardware/software/sensor failure	• RA • RA • UA
Safe Road Trains for the Environment (SARTRE) (2009–2012) (Larburu et al., 2010; Davila et al., 2013; Bergenhem et al., 2010)	• Vehicle platooning and relevant environmental and safety benefits	• RA
VisLab Intercontinental Autonomous Challenge(VIAC) (2010) (Broggi et al., 1999; Broggi et al., 2012; Boudette, 2017; Sorokanich, 2014)	• Vehicle platooning in real traffic situations • Vehicle platooning without *a priori* information • Autonomous driving without *a priori* information	• LA • LA • UA
Grand Cooperative Driving Challenge (2011) (van Nunen et al., 2012; Geiger et al., 2012a)	• Efficient cooperative driving in intersections	• UA
eFuture (2013) (eFuture, 2011)	• Energy-efficient AV technology • Standardized Advanced Driver Assistance Systems (ADAS) • Data fusion for increased perception accuracy • Human acceptance of AVs	• RA • RA • RA • UA
European Truck Platooning Challenge (2016) (Fudge, 2016; van Nunen et al., 2016)	• Real-world platooning using V2V communication	• RA

Grand Challenge was held in 2004. Unfortunately, no vehicle that entered could complete the course. However, in 2005, a second Grand Challenge was held and five vehicles successfully completed the course, providing a great victory for AV research (Buehler et al., 2007).

After the DARPA Grand Challenges, AV research steadily increased (see Fig. 2) (Reuters, 2017) and researchers began to address the challenges of driving in complex and urban environments with dense traffic, complex intersections, and overtaking and lane change maneuvers. Since AV testing on public roads was not yet permitted in many areas, these challenges were difficult to address, as well as test, in real-world situations. The DARPA Urban Challenge, held in 2007, attempted to address this. It consisted of several urban driving scenarios, including an intersection, simulated highway on-ramp, and off-road to on-road route. Moreover, to further simulate a real-world urban environment, the vehicles were required to obey traffic laws (Rouff and Hinchey, 2011). Four vehicles successfully completed the DARPA Urban Challenge, including teams from Carnegie Mellon University, Stanford University, Virginia Polytechnic Institute and State University, and the Massachusetts Institute of Technology. Each of these vehicles used unique sensing,

Table 2
Typical uses, advantages, and disadvantages of common AV sensors.

Sensors and Uses	Advantages	Disadvantages
Single Camera		
• Obstacle detection and classification	• Computationally inexpensive relative to stereovision	•Computationally expensive relative to active sensors (Sivaraman and Trivedi, 2013)
• Lane detection	• Good for classification	• Difficult to measure distances (Rasshofer and Gresser, 2005) (may use optical flow or camera/LIDAR/radar fusion methods (Gruyer et al., 2013))
	• Wide FOV while maintaining good resolution (Rasshofer and Gresser, 2005)	• Velocity information must be calculated
	• Provides additional information about the environment (color, texture, etc.) (Sivaraman and Trivedi, 2013)	• Poor performance in poor weather conditions (Rasshofer and Gresser, 2005)
	• Long range (with high resolution cameras)	• Sensitive to lighting conditions (Sivaraman and Trivedi, 2013)
		• Long range applications require more computation
Stereovision		
• Obstacle detection and classification	• Depth perception similar to human eyes (effective at close range) (Rasshofer and Gresser, 2005)	• Computationally expensive (Huber et al., 2011; Maddern and Newman, 2016)
• Lane detection	• 3D construction	• Velocity and distance information must be calculated
• 3D mapping	• Good for classification	• Poor performance in poor weather conditions (Rasshofer and Gresser, 2005)
	• Provides additional information about the environment (color, texture, etc.) (Sivaraman and Trivedi, 2013)	• Long range applications require more computation
	• Long range (with high resolution cameras)	• Sensitive to lighting conditions (Sivaraman and Trivedi, 2013)
	• Better detection than regular vision	
LIDAR		
• Obstacle detection	• Direct distance measurements	• Poor classification compared to vision (Bacha et al., 2008)
• 3D mapping (with multi-layered LIDAR)	• Large FOV with high resolution and medium range (Rasshofer and Gresser, 2005)	• Velocity information must be calculated
• Lane detection (via intensity measurements)	• Multi-layer LIDAR allows robust 3D construction	• Difficulty detecting highly reflective objects (Leonard et al., 2008)
	• May have internal mechanism to limit the impact of poor weather conditions (Stuff, 2017)	• Typically, poor detection in rain, fog and snow (Rasshofer and Gresser, 2005) (although some LIDAR have countermeasures, such as measuring multiple times per laser pulse (Stuff, 2017))
		• Poor very near (< 2 m) measurement (Rasshofer and Gresser, 2005)
Radar		
• Obstacle detection	• Direct distance measurements	• Long range radar have small FOVs (Rasshofer and Gresser, 2005)
	• Direct velocity measurements (Leonard et al., 2008)	• Poor classification (Leonard et al., 2008)
	• Long-range, mid-range and short-range options available (depending on company) (Henawy and Schneider, 2011; Leonard et al., 2008)	• Poor very near (< 2 m) measurement (Rasshofer and Gresser, 2005)
	• Does well in poor weather conditions (Rasshofer and Gresser, 2005)	• Poor pedestrian detection
	• High accuracy (Rasshofer and Gresser, 2005)	• Poor static object detection
		• Interference of multiple reflections can cause false alarms
Sonar		
• Near obstacle detection (e.g., parking assistance systems)	• Direct distance measurements	• Poor angular resolution (Rasshofer and Gresser, 2005)
	• Very near range (< 2 m) (Rasshofer and Gresser, 2005)	• Poor detection beyond 2 m (Rasshofer and Gresser, 2005)
	• Can operate in fog and snow (Rasshofer and Gresser, 2005)	

perception, and localization techniques to localize the vehicle in the environment and detect, classify and track obstacles (Campbell et al., 2010).

Although the DARPA Urban Challenge tested the AVs in scenarios much closer to everyday driving, these challenges still lacked important and common roadway obstacles, such as pedestrians and cyclists. Additionally, the AVs were not required to detect traffic lights or signs, as these were omitted from the challenge or provided by RNDF files (Buehler et al., 2009; Rouff and Hinchey, 2011). Furthermore, the vehicles drove slowly throughout the challenge (30 mph or less) (Montemerlo et al., 2008).

To address a lack of real-world AV testing, in 2010, the VisLab Intercontinental Autonomous Challenge (VIAC) was initiated. In this challenge, two AVs (a leader and a follower) drove across multiple countries, encountering urban, off-road, and highway scenarios, as well as a myriad of weather conditions. Impressively, the vehicles autonomously drove through these situations with no *a priori* maps or prior knowledge about standard road shapes and sizes for guidance. Instead, the follower vehicle detected the leader

Table 3
Prominent research and commercial vehicle sensors.

Vehicle	Vision	Stereovision	Infrared Camera	LIDAR	Radar	Sonar
Research Vehicles						
Audi' s Research Vehicle (Gitlin, 2016b; Pachal, 2016; Souppouris, 2014)	✓	✓	✓	✓	✓	✓
AutoNOMOS' s MadeInGermany (Volkswagen Passat) (Ghring et al., 2013)	✓	✓		✓	✓	
Carnegie Mellon' s Urban Challenge entry, "Boss" (2007 Chevy Tahoe; 1st place) (Grisleri and Fedriga, 2010; Urmson et al., 2008)	✓			✓	✓	
Ford' s Hybrid Fusion research vehicle (Gitlin, 2016a)	✓			✓	✓	✓
Google' s research vehicles (Toyota Prius; Lexus CT; Custom Google vehicle) (Google, 2017; Guizzo, 2011; Vanderbilt, 2012)	✓	✓		✓	✓	
LIVIC' s "CARLLA" (Vanholme et al., 2013) (information also gathered by personal interviews with LIVIC labs)	✓			✓	✓	
MIT' s Urban Challenge entry, "Talos" (Land Rover LR3; 4th place) (Leonard et al., 2008)	✓			✓	✓	
Nagoya and Nagasaki University' s Open ZMP Robocar HV (Toyota Prius) (Kato et al., 2015)	✓			✓		
Stanford' s Urban Challenge Entry, "Junior" (2006 Volkswagen Passat; 2nd place) (Levinson et al., 2011; Montemerlo et al., 2008)				✓	✓	
Virginia Tech' s Urban Challenge entry, "Odin" (2005 Hybrid Ford Escape; 3rd place) (Bacha et al., 2008)				✓		
VisLab' s "BRAiVE" (Grisleri and Fedriga, 2010; VisLab, 2010)	✓	✓		✓		
Volvo' s research vehicle (Stoklosa, 2015; Cars, 2016)	✓		✓	✓	✓	✓
Commercial Vehicles						
2015 Infiniti Q50S (Sherman, 2016)	✓				✓	✓
2016 Lexus RX (Lexus, 2017; Vandezande, 2013)	✓				✓	✓
2016 Volvo XC90 (Volvo, 2016)	✓				✓	✓
BMW750i xDrive (BMW, 2017; Sherman, 2016)	✓	✓	✓		✓	✓
Ford (high-end production vehicles) (Company, 2014)	✓				✓	✓
Mercedes-Benz E and S-Class (Sherman, 2016; Tingwall, 2013; Ulrich, 2014; Mercedes-Benz, 2013; Vanderbilt, 2012)	✓	✓	✓		✓	✓
Otto Semi-Trucks (Stewart, 2016)	✓	-		✓	✓	
Renault GT Nav (Renault, 2017)	✓				✓	✓
Tesla Model S (Golson, 2016; Sherman, 2016)	✓				✓	✓

'–' denotes unspecified/unidentified information.

Note: Not all vehicles were included in this table due to the fast growth and vastness of the industry and research in this area.

Table 4
Available autonomous features in high-end commercial vehicles.

Vehicles	Autonomous Freeway Driving	Autonomous Lane Change	Semi-Autonomous Parking	Semi-Autonomous Braking
BMW750i xDrive (BMW, 2017; Sherman, 2016)	✓		✓	✓
Ford (high-end production vehicles) (Company, 2014)	✓		✓	✓
2015 Infiniti Q50S (Sherman, 2016)	✓			✓
Lexus RX (Lexus, 2017)			✓	✓
Mercedes-Benz E and S-class (Sherman, 2016; Mercedes-Benz, 2013; Ulrich, 2014; Tingwall, 2013; Vanderbilt, 2012)	✓		✓	✓
Otto Semi-Trucks (Stewart, 2016)	✓			✓
Renault GT Nav (Renault, 2017)			✓	✓
Tesla Model S (Golson, 2016; Sherman, 2016)	✓	✓	✓	✓
Volvo XC90 (Volvo, 2016)	✓		✓	✓

vehicle and applied platooning techniques to drive across several European and Asian countries (Broggi et al., 2010, 2012).

Unlike the vehicles in many past road tests (e.g., in the "Munich to Odense UBM Test" and the "No Hands Across America" test (Maurer et al., 1996; Pomerleau, 1995)), many AVs today, such as Google' s AVs, are heavily reliant on *a priori* information, including *a priori* maps (Boudette, 2017; Sorokanich, 2014). *A priori* maps are detailed, static records of the surrounding environment, which alleviate the high computational load of mapping the environment in real-time. For reference, to build an *a priori* map a human will pre-drive the desired route, and following this, the vehicle will autonomously drive this route using the previously collected data. The AV system can then focus primarily on providing accurate localization, as well as detecting and reacting to obstacles. However, *a priori* information can limit the AVs ability to adapt and react safely to new situations such as new construction zones, potholes, and stoplights (Sorokanich, 2014). Since common environmental changes can drastically affect a vehicle' s ability to rely on these pre-made maps, other localization and mapping methods in real-time are being researched. This topic is discussed in detail in Section 4.

Connected vehicle technology, such as vehicle-to-infrastructure (V2I) and vehicle-to-vehicle (V2V) communication, may be able

Table 5
Prominent research vehicles' localization and mapping methods.

Research Vehicles	*A priori* method	SLAM-based method
Audi' s research vehicle (Gitlin, 2016b; Pachal, 2016; Souppouris, 2014)		✓
AutoNOMOS Labs' "MadeInGermany" (Wang et al., 2011a)	✓	
Braunschweig University of Technology' s "Leonie" (Saust et al., 2011)	[a]	✓
Bundeswehr University of Munich' s "VaMP" (Maurer et al., 1996)		✓
Carnegie Mellon' s "NavLab" in "No Hands Across America" (Thorpe et al., 1988)		✓
Carnegie Mellon' s Urban Challenge entry, "Boss" (1st place) (Grisleri and Fedriga, 2010; Urmson et al., 2008)	[a]	✓
Ford' s Hybrid Fusion research vehicle (Gitlin, 2016a)	✓	
General Motors' research vehicles (Davies, 2016)	✓	
Google' s research vehicles (Google, 2017; Guizzo, 2011; Vanderbilt, 2012)	✓	
Honda' s research vehicle (Betters, 2015)	✓	
Karlsruhe Institute of Technology' s "Bertha Benz" (Ziegler et al., 2014)	✓	
LIVIC' s "CARLLA" (Vanholme et al., 2013) (information also gathered by personal interviews with LIVIC labs)		✓
MIT' s Urban Challenge entry, "Talos" (4th place) (Leonard et al., 2008)		✓
Nagoya and Nagasaki University' s Open ZMP Robocar HV (Kato et al., 2015)	✓	
nuTonomy' s vehicles (Hodson, 2016)	✓	
Oxford University' s "Wildcat" (Hawkins et al., 2011)	[a]	✓
Stanford' s "Shelley" (Broggi et al., 2014)	✓	
Stanford' s Urban Challenge entry, "Junior" (2nd place) (Levinson et al., 2011; Montemerlo et al., 2008)	[a]	✓
Toyota' s research vehicle (Betters, 2015)	✓	
Uber' s vehicles (Insider, 2017)	✓	
University of Parma' s "ARGO" (Broggi et al., 1999)		✓
Virginia Tech' s Urban Challenge entry, "Odin" (3rd place) (Bacha et al., 2008)	[a]	✓
VisLab' s "BRAiVE" (Broggi et al., 2013; Grisleri and Fedriga, 2010; VisLab, 2010)		✓
Volvo' s research vehicle (Stoklosa, 2015; Cars, 2016)	✓	

[a] Heavily reliant on certain *a priori* information, but not highly detailed, pre-created maps.

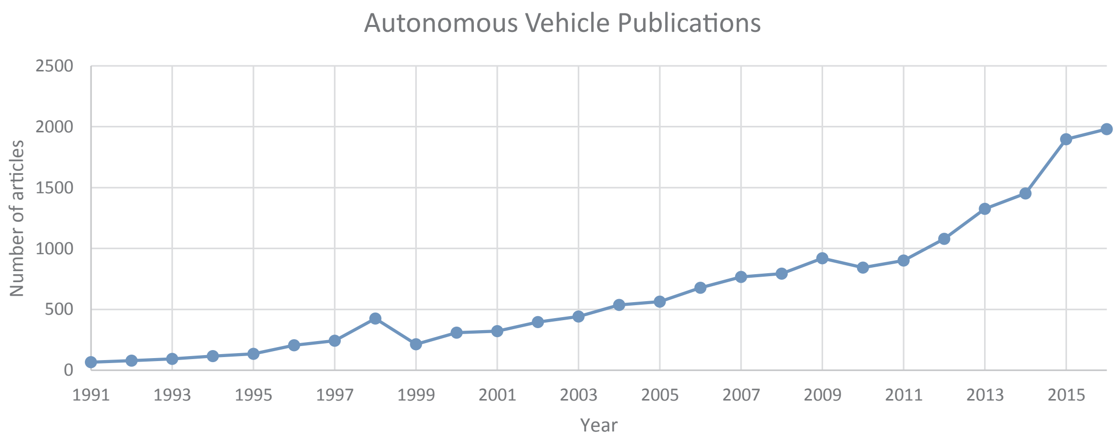

Fig. 2. Number of articles in the Web of Science database (Reuters, 2017) containing the keywords 'autonomous' and 'vehicle' from 1991 to 2016. Note that as the Web of Science collects more articles, the data for recent years (2016, 2015, 2014, …) may increase. Era I, Era II, and Era III refer to the different stages of autonomous vehicle events and challenges as described in Fig. 3.

to resolve some of the existing problems resulting from heavy reliance on *a priori* information. V2I communication could provide a network for intersections, road signs and construction signs to transfer important infrastructure information, such as road layout changes, speed limits, and traffic light information to AVs (Barrachina et al., 2013; Ilgin Guler et al., 2014). Similarly, V2V communication allows vehicles to share data, such as vehicle state, positioning, or intention to change lanes, with other vehicles (Dang et al., 2014; Dey et al., 2016). By integrating V2V and V2I communication with autonomous vehicle technology, an effective "co-operative driving" network can be established (Barrachina et al., 2013; Kaviani et al., 2016).

In 2011, a challenge in the Netherlands called the "Grand Cooperative Driving Challenge" (GCDC) aimed to accelerate "co-operative driving" technology. In this event, teams of AVs cooperatively drove along a contained highway and intersection, transmitting signals to each other to indicate their intentions. The event' s objective was to complete the challenges quickly (in terms of throughput), fuel-efficiently, and stably through employing V2V and V2I communication (Geiger et al., 2012a; van Nunen et al., 2012). A more recent challenge, the 2016 European Truck Platooning Challenge, also explored V2V technology, aiming to encourage the development self-driving, connected vehicles. In this challenge, autonomous vehicles platooned behind human-driven vehicles from cities in Sweden, Germany and Belgium to Rotterdam in the Netherlands. This challenge allowed V2V communication to be employed and tested in a real-world, large-scale environment (van Nunen et al., 2016; Fudge, 2016).

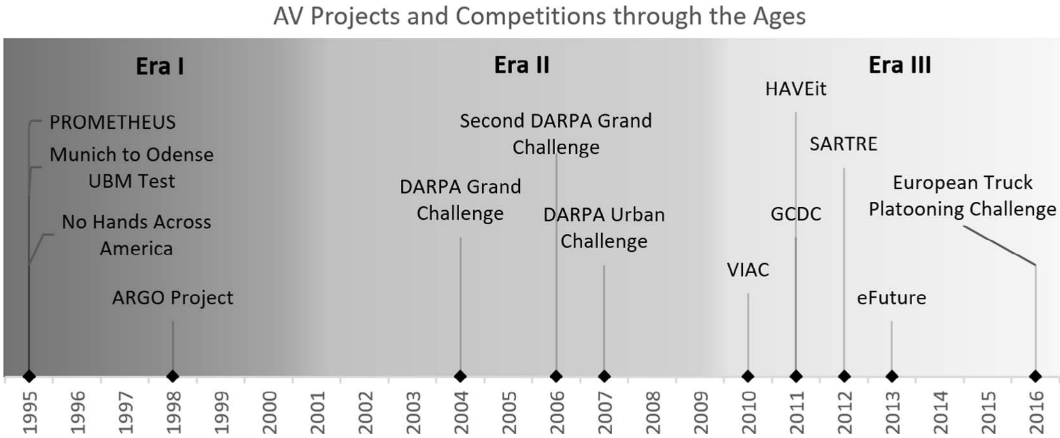

Fig. 3. Significant road tests and AV challenges from 1995 to 2016. Era I is characterized by long distance highway road tests, Era II is characterized by DARPA challenges towards complex, unaided autonomous driving, and Era III is characterized by connected vehicle and platooning road tests.

Other influential projects include the Programme for European Traffic with Highest Efficiency and Unprecedented Safety (PROMETHEUS) (Eureka, 1995), Safe Road Trains for the Environment (SARTRE) (Larburu et al., 2010), Highly Automated Vehicles for Intelligent Transport (HAVEit) (Vanholme et al., 2013), and eFuture (eFuture, 2011) projects. The PROMETHEUS project, which ran from 1987 to 1995, combined the technical knowledge and skills of universities, electronics manufacturers, and car companies from across Europe to develop early AVs. The project included a range of topics from collision avoidance systems to cooperative driving to vehicle environmental sustainability (Eureka, 1995; Oagana, 2016). A significant prototype developed in this project was the ProLab2 vehicle, which used a perception and copilot system to monitor the environment and develop warnings signals for a human driver. This project was quite advanced for its time, incorporating static and dynamic environments, data fusion, decision-making, and human-machine interface research (Amin et al., 1995; Eleter and Rombaut, 1996).

The SARTRE project, which ran from 2009 to 2012, was a large-scale connected-vehicle project. In this project, aspects of vehicle platooning, from the strategies and safety benefits of vehicle platooning to the efficiency and aerodynamics of vehicle platooning, were investigated. A major outcome of this project was the development and implementation of safe connected, AV platoons, which drove in various European countries including Sweden and Spain Bergenhem et al. (2010), Davila et al. (2013) and Larburu et al. (2010). Furthermore, the HAVEit project, which ran from 2008 to 2011, aimed to improve the safety, efficiency and comfort of driving. This project produced safety architecture software to manage smart actuators, cooperative driving communication and redundancy data; a co-system to increase human driving safety by assessing the driver' s state (e.g., drowsy, alert, stressed, etc.); and highly automated driving systems, which included automated queue and congestion assistance, temporary auto-pilot, and active green driving systems (HAVEit, 2008). Most recently, the eFuture project, which ran from 2010 to 2013, aimed to develop energy efficient advanced driver assistance system (ADAS) technology with standardized interface and signal definitions (eFuture, 2011). These projects focused on the development of important areas of autonomous and semi-autonomous vehicle advancement including cooperative driving, driver monitoring, and methods to improve the energy efficiency of driving.

Although each of these challenges and projects (see Fig. 3) developed promising advances in AV technology, industrial leaders, such as Google and Tesla, acknowledge that AVs are not yet robust enough to drive without human supervision (Eddy, 2016; Tesla, 2016). Nonetheless, the human aspect of driving is the root cause of most accidents (Lu et al., 2016). As mentioned previously, in 2015, an estimated ninety-four percent of motor vehicle accidents in the United States were due to human-related causes (such as distraction, drowsiness, inattention and emotion) (Singh, 2015). Thus, in order to reduce motor vehicle accidents, the human aspect of driving should be improved through monitoring or co-pilot systems (as in the HAVEit and eFuture projects), or entirely removed through fully autonomous systems. In conclusion, to attain the full potential of such autonomous systems, the chief remaining perception challenges include:

- AV perception in poor weather and lighting conditions
- AV perception in complex urban environments
- Autonomous driving without heavy reliance on *a priori* perception data
- Utilization of connected vehicle technology to improve accuracy, certainty and reliability of perception
- Development of safety measures in case of faulty sensors/perception

A summary of the challenges exposed by the AV projects and competitions is provided in Table 1. This table also provides information about the extent to which each problem has been addressed (as of the time of publication of this paper), which may be used to guide future research.

3. Perception and automotive sensors

Similar to human drivers, AVs must be able to continuously observe their surroundings and accurately calculate their location on both a local (relative to the curb, obstacles, intersections, etc.) and global (which street, neighborhood, city, etc.) scale. To provide AVs with these abilities, sensors are installed in and around the vehicle.

3.1. Automotive sensor technology overview

As an overview, automotive sensing falls into three main categories: self-sensing, localization, and surrounding-sensing (Maurer et al., 2016; Vanholme, 2012). Self-sensing uses proprioceptive sensors to measure the current state of the ego-vehicle, including the vehicle' s velocity, acceleration, yaw, and steering angle. Proprioceptive information is commonly determined using pre-installed measurement units, such as odometers, inertial measurement units (IMUs), gyroscopes, and information from the controller area network (CAN) bus. Localization, using external sensors such as GPS or dead reckoning by IMU readings, determines the vehicle' s global and local position. Lastly, surrounding-sensing uses exteroceptive sensors to perceive road markings, road slope, traffic signs, weather conditions, the state (position, velocity, acceleration, etc.) of obstacles including other vehicles, and even the state of the driver (vigilance, drowsiness, fatigue, boredom due to monotony, etc.) (Vanholme, 2012).

Proprioceptive and exteroceptive sensors can be categorized as either active or passive sensors (Vanholme, 2012). Active sensors emit energy in the form of electromagnetic waves and measure the return time to determine parameters such as distance. Examples include sonar, radar, and LIght Detection And Ranging (LIDAR) sensors. Passive sensors do not emit signals, but rather perceive electromagnetic waves already in the environment (e.g., light-based and infrared cameras). Determining which sensors or combination of sensors that are best suited for AV applications can be difficult. Therefore, before choosing a specific sensor or a combination of sensors, it is important to consider design factors such as: (1) the proprioceptive or exteroceptive sensor information required, (2) whether a passive or active sensor should be used, (3) budget, and (4) whether to use a single sensor or multiple sensors.

Localization typically uses a combination of sensors such as GPSs, IMUs, odometers, and cameras (by matching between primitives and a map, i.e., SLAM) for high precision results (Levinson and Thrun, 2010; Marais et al., 2014; Vanholme, 2012; Wolf and Sukhatme, 2004). Data fusion from multiple sensors can minimize shortcomings of individual sensors and increase the reliability and robustness of the system (Bresson et al., 2016; Gruyer et al., 2015). Depending on budget, sensors used for localization can range from a very expensive, highly accurate and precise GPS (RTK) and IMU (with fiber optics) system or a combination of less expensive GPS and IMU sensors coupled with other technologies, such as 3D obstacle detection systems (Obst et al., 2012). For production vehicles, developers commonly aim to minimize cost and maximize safety; thus, the second method is often used.

The combination of low-cost IMUs, which can localize reliably for short periods of time (such as through tunnels), and GPSs, which can localize reliably for long periods of time, but may lose connection when in remote areas or through tunnels, can effectively reduce positioning errors and provide localization information during GPS outages (Sasiadek and Wang, 2003). This is a classic example of multisensor fusion (Kaviani et al., 2016), which will be discussed further below. One example of such multisensor fusion in the literature includes (Gruyer et al., 2016a), in which researchers fuse GPS, INS, road marking detection, and road marking map information to achieve sub-decimeter positioning accuracy. Another example includes (Bresson et al., 2016), in which researchers fuse various levels of data (e.g., direct sensor information, algorithm output, high-level object information such as obstacle dynamics and road markings, etc.) to provide improved positioning accuracy.

In general, AV developers use different combinations of light-, sound-, and/or vision-based sensors for detection of the vehicle' s surroundings. These sensors can be either passive or active with most current passive sensors being less expensive than active sensors, such as the active sensor, LIDAR (Ros et al., 2015; Sun et al., 2006). However, active sensor (specifically LIDAR) prices may be dramatically decreasing with the advent of start-up companies, such as Innoviz (Ackerman, 2016a), which aims to develop a low cost LIDAR (less than $100.00 USD), and large investments into the LIDAR company, Velodyne (Vincent, 2016). Additionally, as the development of AV technology using active sensors increases, active signals may begin to interfere with each other (Bertozzi et al., 2000; Sun et al., 2006), making these sensors impractical. For instance, in high-density traffic conditions, radar systems may pick up other vehicles' radar signals, causing false detections, interference and additional uncertainty (Hischke, 1995; Schipper et al., 2015). Vision-based systems do not face this challenge, which is a key factor leading some researchers to focus on vision as a primary perception mode for future AV systems (Bertozzi et al., 2000; Ranft and Stiller, 2016; Sivaraman and Trivedi, 2013).

Nevertheless, vision-based systems have their own shortcomings. A key concern with vision-based systems is that computing distance information requires complex algorithms, whereas active sensors can directly determine this information with high accuracy. Stereovision (which consists of two cameras mounted at a horizontal distance from one another) can provide 3D information such as depth; however, when the point of interest is far away (e.g., on the horizon), the images collected by each camera become effectively the same, and are no longer able to provide the required information for 3D perception (Gu, 2014). As well, the computational complexity of creating a 3D space using stereovision (computation of a disparity map) is much larger than creating 3D space using 3D LIDAR systems, such as the Velodyne HDL or Ibeo LUX (Huber et al., 2011; Maddern and Newman, 2016).

For more information about the advantages and disadvantages of common passive and active sensors, please refer to Table 2. The purpose of this table is to provide a general overview of common AV sensors for newcomers to AV research. It also may be useful as a quick reference point for presentations. Research and development in the area of AV sensors is intense. New products with higher accuracies and better performances are introduced on almost a daily basis. The reader is encouraged to use this guide as a starting point and check the state-of-the-art. For example, new generation LIDAR and radar, such as the solid-state (or phased array) LIDAR (Duffy, 2017; Ackerman, 2016b), may not generally be used in AVs today, but the reader is encouraged to investigate such technology further.

To compensate for individual shortcomings, sensors can be coupled via "multisensor fusion." Multisensor fusion's benefits, including improving perception accuracy, reliability, and robustness, are widely known and used in AV research (Dasarathy, 1997; Kaviani et al., 2016; Sasiadek and Wang, 2003; Gruyer et al., 2016a; Bresson et al., 2016). As mentioned previously, a classic multisensor fusion example is GPS/INS fusion (Kaviani et al., 2016). Another example of multisensor fusion includes combining camera and LIDAR sensor data (Ashraf et al., 2017). In Daraei et al. (2017), LIDAR and camera data is fused to decrease uncertainty and increase detection accuracy. Combining sensor data from multiple different sensors with an identical field of view is an example of competitive fusion (Durrant-Whyte, 1990). LIDAR and camera data can also be fused purely for calibration purposes (Zhou, 2014). For example, the depth information from the LIDAR can be used to efficiently find a projection matrix between the vision and LIDAR sensors (Park et al., 2014).

Sensor fusion is also not restricted to fusing data from multiple sensors. Sensor fusion can also be performed by fusing data from multiple readings of a single sensor to obtain a more reliable output (Elmenreich, 2002). However, in general and in a more traditional sense, one may choose two identical sensors with an identical scope of work to make the system more reliable through system redundancy. This is called competitive fusion (Durrant-Whyte, 1990). One can also use two complementary sensors to increase coverage. For example, using complementary LIDAR on either side of a vehicle to cover a wider angle ahead of the vehicle (Durrant-Whyte, 1990).

Sensor fusion is widely used for a number of reasons including more reliable data outcomes, more coverage, applicability, and above all, lower initial investment (equipment cost) though at a higher computation cost. The lattermost reason is often why sensor fusion is preferred over using single, highly accurate sensors. The initial monetary cost of a highly accurate sensor is generally significantly higher than the cost of two low-cost sensors, which can generally achieve similar or better results to single sensor algorithms via sensor fusion (Leonard et al., 2008; Suhr et al., 2017; Sanchez-Lopez et al., 2016; Park et al., 2017). It can be mathematically proven that the covariance of measurements of two sensors is less than that of both of them regardless of their individual variances (Maybeck, 1979). Nonetheless, the use of highly accurate sensors is generally a good thing regardless of them being fused to other sensors, provided the cost is still affordable for automotive applications.

To further illustrate the usefulness of sensors based on their accuracy and cost, consider the IMU. An cost effective IMU ($10–$100) alone is generally not accurate enough for any robotics or AV applications, but can be used in a sensor fusion system to increase accuracy to a useful level. A mid-level IMU ($1000–$2000) may be sufficient for certain navigation problems (short-term motion estimation), but it is neither accurate enough to be used as a sole sensor (i.e., dead reckoning) nor affordable for widespread AV use. Finally, high-end IMUs (>$10000), which are often used in aircrafts, are quite accurate, but remain beyond the reach of AV applications due to high initial costs (Douxchamps, 2017).

The sensor arrangements chosen for AV research and commercial vehicles are noticeably linked to the vehicles' specific autonomous application and desired maneuvers. For example, the vehicles in the DARPA Urban Challenge were generally outfitted with multiple, expensive LIDAR and radar sensors, but lacked sonar sensors, since the challenges did not focus on low-speed, precise maneuvers (such as parallel parking). Conversely, many production vehicles, such as the Tesla Model S and the Mercedes-Benz S class, include ultrasonic (sonar) sensors for parking maneuvers, but do not use LIDAR, due to current high costs. Infrared cameras, which are used to detect pedestrians and other obstacles at night, are predominantly found on production vehicles, possibly since research vehicles may primarily drive during the day. Other commercial vehicles, such as Renault, Volvo, and Audi, use Mobileye technology. This technology consists of multiple mono-cameras with different focal points. It is affordable and efficient for motorways, albeit less effective in suburban and urban situations (Gitlin, 2016c). For more information on sensor arrangements in prominent research and commercial vehicles, see Table 3.

Furthermore, Table 4 provides an overview of the autonomous features available in commercial vehicles. (Note that since research vehicles are continually evolving as different research topics are investigated, it is difficult to know which features a vehicle may have at any point in time; thus, a table for autonomous research vehicle features was omitted.) Currently, many research vehicles are being tested with level three autonomy (limited self-driving automation (NHTSA, 2013)) whereas the high-end commercial vehicles are generally available with level one or two autonomy (function-specific automation or combined function automation (NHTSA, 2013)) and contain different autonomous and semi-autonomous features.

3.2. Areas for automotive sensor and perception improvement

Even though sensor technology has rapidly advanced, there are still many areas that require improvement before level five autonomy can be achieved. Three major challenges related to sensor technology that remain unresolved are: (1) perception in poor weather conditions, (2) perception in changing and unfavorable lighting conditions and (3) human perception of automotive sensors.

3.2.1. Perception in poor weather conditions

Perception in poor weather conditions such as snow, heavy rain, and fog is an important AV research topic as these scenarios continuously prove to be problematic even for human drivers. In snowy conditions, it has been found that both vision-based and LIDAR-based systems have extreme difficulty (Rasshofer and Gresser, 2005). Many vision-based AVs rely on observing the road markings to navigate the roads. However, a thin layer of snow can cause these markings to completely disappear, making navigation difficult. Furthermore, even obscured, dirty, worn or painted-over road markings (without snowy conditions) can cause difficulty for the AV' s perception system (Rebut et al., 2004). In addition, the "heaviness" or density of the snow has been found to affect the LIDAR beams causing reflections off snowflakes producing "phantom obstacles" (Radecki et al., 2016). These "phantom obstacles" can inhibit the AV' s ability to correctly judge the environment and may cause the vehicle to mistakenly stop. In rainy or foggy conditions, similar difficulties arise. LIDAR has been found to detect rainwater splashing upwards from behind vehicles as phantom obstacles, and fog can obscure the cameras' views, inhibiting the ability to reliably perceive the vehicle' s surroundings (Rasshofer and Gresser, 2005).

As noted in Table 2, radar generally performs well in poor weather conditions. However, autonomous driving cannot rely purely on radar for perception due to the radar' s inability to perform robust classification and detect road markings. A potential solution to the challenges posed by driving in poor weather conditions may instead lie in vision algorithm improvement. Since humans can drive safely in rain and snow using only their eyes for perception, algorithms that mimic biological vision have the potential to allow for safe autonomous driving in heavy rain or snow. An introduction to such 'biomimetic' vision can be found in Denuelle and Srinivasan (2015), Lowry et al. (2016), Safwan et al. (2013) and Wang et al. (2011b); however, current research (to the best of the authors' knowledge) does not yet address biomimetic vision for navigation in poor weather conditions.

In Radecki et al. (2016), sensor fusion of camera, LIDAR, and radar sensors was used to detect pedestrians and vehicles in cloudy, sunny, snowy, rainy, and dark conditions. However, according to the authors, the system still requires improvement to robustly and consistently detect obstacles under these conditions. This may be completed by using additional sensors or utilizing connected vehicle technology to further validate sensor data. Other techniques, such as using stereovision and scene priors (Gehrig et al., 2013) or relying on taillight recognition (Cui et al., 2015), may address this problem.

3.2.2. Perception in changing and unfavorable lighting conditions

Lens-flares, large shadows and other unfavorable lighting conditions also present difficulties for perception. For example, vision systems may confuse large shadows to be parts of other objects (Balan et al., 2007). Furthermore, different visual cues (such as taillights, reflective road markings, etc.), and/or thermal imaging (far-infrared) cameras may need to be added to current perception systems to enhance performance in low-light conditions or at night (Borkar et al., 2009; Hurney et al., 2015; Schamm et al., 2010). Nonetheless, even systems using such technology can have difficulty detecting and tracking obstacles. According to Hurney et al. (2015), a significant amount of far-infrared camera detection and tracking algorithms are not computationally efficient enough to be used in real-time.

Other perception systems attempt to address light condition problems by relying on *a priori* information about the environment. Stanford updated their research vehicle, Junior, to be able to detect traffic lights in differing lighting conditions using an *a priori* list of traffic light locations (Levinson et al., 2011). Nevertheless, relying on *a priori* information can cause problems when there are changes to the environment. For example, if a new traffic light was installed without Junior' s *a priori* list being updated, the vehicle would not attempt to detect it (Levinson et al., 2011).

Other methods may instead rely on active sensors, such as LIDAR, to overcome the lighting condition problem. Such sensors do not require external light for perception, allowing them to detect obstacles in poor light and at night (Jo et al., 2017). Nonetheless, LIDAR data often contain noise when observing complicated or deeply textured objects, such as bushes, hindering the system' s perception (Jo et al., 2017). Thus, to better address the lighting condition problem, data from multiple sensors, such as cameras and LIDAR sensors, can be combined, contributing different advantages in poor lighting conditions to achieve better results (Jo et al., 2017; Radecki et al., 2016). Although researchers have attempted to address driving in poor lighting and weather conditions, it is evident that extensive research is still required to resolve the remaining challenges before vehicles can reliably drive in such conditions.

3.2.3. Human perception of automotive sensors

In order for autonomous features to effectively increase safety, there must be a certain level of public acceptance and understanding of AV technology, including an understanding of the capability of AV sensors. As discussed previously, automotive sensors are integrated into vehicles to assist human drivers with tasks such as detecting obstacles, maintaining a set speed, and emergency braking. When humans do not understand the capability of sensors or the sensors are insufficient for the driving task, the human driver may either rely too much on the sensor or disregard the sensor's readings entirely. Thus, it is important for sensors to be sufficient for the driving task and as capable and robust as possible. Furthermore, human drivers must be informed of the capability of sensors to prevent misunderstandings that could potentially cause accidents.

To further illustrate the need for improved sensors as well as increased public understanding, the following example is provided. Long-range automotive radar, which typically has the longest range of all AV active sensors, only has a range of 4.5–7.5 s at highway speeds (150–250 m range (Henawy and Schneider, 2011; Rasshofer and Gresser, 2005) at a speed of 120 km/h). According to ICBC standards, human drivers are instructed to look at least twelve seconds ahead to ensure safe driving (British Columbia (ICBC), 2015). When solely comparing these numbers, the sensors seem insufficient. However, since computers have the ability to react much faster than humans do, the current state-of-the-art sensor ranges (especially when supplemented with vision, which can detect obstacles further down the road) are generally sufficient for safe driving, as shown by Google and Tesla' s excellent driving records (Levin and Harris, 2017).

Thus, even though sensor ranges may in fact be sufficient, it is important to ensure the public understands the technology' s capacity (e.g., its ability to adequately detect obstacles in typical conditions) as well as its limitations (e.g., its inability to detect obstacles past a certain distance or in poor weather conditions). According to Kyriakidis et al. (2017), the public may not be able to benefit from intermediate stages of autonomous driving (e.g., Level 2 and 3 autonomy, in which the driver is still required to take control of the vehicle) since drivers may not understand the autonomous features' extent and limitations and therefore may not safely regain control of the driving tasks when necessary. Furthermore, studies have found that many drivers prefer to have full control of the driving task (Kyriakidis et al., 2015, 2017); thus, consumers may not utilize autonomous features thereby also declining to utilize the safety benefits of such technology. The technology behind AVs may continue to evolve rapidly, but human perception of the technology may limit its reach and benefits. An example illustrating the importance of the public' s perception of AV sensors and the robustness of these sensors includes the fatal crash on May 7, 2016 involving Tesla' s autopilot. In this accident, the autopilot' s vision system failed to see a semi-truck trailer against the white sky. Furthermore, the driver, who likely assumed the autopilot system could detect all obstacles on the road, failed to take control of the vehicle, resulting in a fatal collision (Greenemeier, 2016).

Evidently, it is important to ensure that the sensors being used are as capable and robust as possible, and that the public understands the benefits of AV technology and how to use this technology effectively. Nonetheless, since the vast topic of human factors (HF) in automation is outside the scope of this paper, additional articles of interest that address this topic include (Bansal et al., 2016; Folsom, 2011; Schoettle and Sivak, 2014; Vagia et al., 2016), which investigate the public' s opinion and/or social ramifications of autonomous driving features, and (Banks and Stanton, 2016b,a; Heikoop et al., 2016; Kim and Yang, 2017; Lu et al., 2016; Mok et al., 2015; Ohn-Bar and Trivedi, 2016; Payre et al., 2016; Saito et al., 2016; Stanton et al., 2007), which analyze the safety and effectiveness of drivers' interactions with autonomous features.

Although many commercial and research vehicles contain varied sensor combinations to increase perception reliability and robustness, much work still needs to be done before level five autonomy is completely achieved. Sensor reliability in poor weather conditions, sensor cost (especially active sensor cost), and the public' s understanding of autonomous sensors and systems must improve before fully autonomous commercial vehicles should be available for public use. Furthermore, monitoring systems must be developed to detect and identify system failures (e.g., faulty sensors/actuators, algorithmic errors) and degraded operating conditions to ensure the AV' s sensors are working correctly while on the road. Although this topic is not the focus of this paper, it will be briefly discussed in the next section, as it is important to consider when developing any AV technology.

3.3. Sensor failure and operating condition monitoring

Once AVs can robustly perceive the environment, they will also need to be able to detect and identify sensor and perception failures and/or degradations. An analogy can be made between a human driver perceiving an illuminated engine light and deciding to safely pull over, and an AV determining that one of its sensors is compromised and safely maneuvering the vehicle off the road.

To address this difficulty in aerospace systems, often multiple identical sensors are incorporated to increase redundancy, validate each sensor' s correct operation through comparison, and thus determine whether any of the sensors are faulty. However, duplicating sensors can be costly and inefficient (Simani, 2003). Thus, other fault detection and isolation (FDI) methods have been proposed, such as using an observer (or system model) to determine whether a drone' s current behavior is significantly different from its fault-free behavior (Heredia et al., 2008; Simani, 2003).

In autonomous road vehicle studies, researchers have found some success using similar model-based methods (Huang and Su, 2015; Jaradat et al., 2013; Shrivastava and Rajamani, 2001); however, these methods require "near-perfect" system models in order to be effective (Pous et al., 2017). Moreover, finding a "near-perfect" AV system model is extremely difficult due to the nonlinearity of vehicle maneuvers and unpredictability of the vehicle' s surrounding environment (Pous et al., 2017). Thus, in real-world situations, model-based FDI methods may not be effective.

An alternative proposed in Pous et al. (2017) uses analytical redundancy and nonlinear transformation methods to compare sensor metrics in order to detect and identify faulty or deviant sensors. In this application, the false alarm rate for sensor faults is low; however, the missed detection rate is high. Thus, continued research into FDI methods that do not rely on near-perfect system models, yet correctly detect, and identify faults is encouraged.

3.4. Perception Algorithms

This section provides a brief, high-level overview of algorithms currently used in AV perception. Note that this paper does not aim to review or survey perception algorithms in detail (other papers, including (Sivaraman and Trivedi, 2013; Viswanathan and Hussein, 2017; Javaheri et al., 2017; Nguyen and Le, 2013; Geiger et al., 2012b; Sun et al., 2006) do so already), but to provide an overview for newcomers to the AV field. At the highest level, perception algorithms can be separated into three categories: mediated perception, behavior reflex perception, and direct perception. In mediated perception, algorithms develop detailed maps of the AV's surroundings through analyzing distances to vehicles, pedestrians, trees, road markings, etc. This is the most common AV perception technique used in research today. Conversely, behavior reflex perception algorithms use artificial intelligence techniques to map sensor data (e.g., an image of the vehicle's environment) directly to driving maneuvers. The third category, direct perception, combines the artificial intelligence of the behavior reflex approach with the metric collection of the mediated perception approach. This approach is a newer concept and discussed in more detail in Section 4.4 (Chen et al., 2015). In addition to these three paradigms, perception algorithms may be categorized as vision-based algorithms, point-cloud based algorithms, or a mixture of the two (through using fusion techniques, as discussed in Section 3.1). Vision-based perception relies predominantly on camera data. Thus, these algorithms dissect pixel-based video to detect vehicles, pedestrians, and other obstacles in the environment. Algorithms may use geometry, optical flow, color, or other image characteristics for detection (Sivaraman and Trivedi, 2013). Point-cloud based perception relies predominantly on data from points (or distances measured to objects) in 3D space collected by active sensors. The algorithms may involve deriving structure from masses of points through the density, geometry or pattern of the points in order to detect objects (Nguyen and Le, 2013).

4. Localization and mapping

Localization and mapping has been a popular research topic for many years. It has evolved from stationary, indoor mapping for mobile robot applications, to outdoor, dynamic, high-speed localization and mapping for AVs. The initial problem researchers faced was determining how to measure the environment while moving to create reliable and accurate maps for successful navigation through indoor areas. This required the robot to determine where it was relative to obstacles and walls while simultaneously creating (and storing) an accurate map. This process became known as Simultaneous Localization and Mapping (SLAM) (Durrant-Whyte and Bailey, 2006).

4.1. Initial algorithms

Initial SLAM algorithms were generally variants of occupancy grid maps or topological/feature-based maps (Leonard et al., 1992; Lowry et al., 2016). Occupancy grid maps provide the likelihood of the presence of an obstacle in each gridline of space. The following steps are generally completed in such grid map algorithms: (1) the robot senses for obstacles, (2) the likelihood of obstacles' presence is increased or decreased on the grid depending on whether an obstacle was detected, (3) the robot localizes itself on the grid using odometry and sensed distance-to-landmark information, (4) the robot moves somewhere else in the space, and (5) the process is repeated until a complete map is created or the robot' s goal is reached (Biswas et al., 2002; Leonard et al., 1992; Stepan et al., 2005). A similar process is implemented for feature-based maps; however, the amount of information collected is selective and data storage is much more efficient. Instead of storing a large grid containing everything in the space, only features or landmarks and the relationship between these landmarks (such as distance) are stored (i.e., object "states") (Leonard et al., 1992).

After the initial SLAM problem was solved, the next difficulty was determining whether obstacles were dynamic or stationary. In initial SLAM algorithms, once a robot recognized an obstacle, the robot would always avoid that area on the map, regardless if it was a stationary or moving object. To address this challenge, algorithms needed to determine not only the likelihood of an object actually being there (depending on the reliability and accuracy of the robot' s sensors), but also the likelihood of an obstacle being there in the future. One early method used a feature-based map that determined where features were presently, and predicted where objects would move in the next algorithmic cycle (Leonard et al., 1992).

To move towards AV localization and mapping, researchers began developing road-based algorithms. These were initially based on robotic SLAM algorithms; however, important differences between robotic and road vehicle mapping (such as the environment surrounding the vehicle and the speed of the vehicle) became apparent. Specifically, the majority of the robotic algorithms were designed to map indoor, highly structured, well-lit environments, rather than outdoor, variably-lit, road-based environments (in which AVs need to localize themselves globally (on the earth) as well as locally (on the road)). Furthermore, AVs operate at highway-speeds, rather than indoor walking speeds, which require faster and more efficient mapping algorithms.

4.2. Global and local localization

Unlike indoor robots, AVs must be able to: (1) globally localize themselves in order to drive from one part of the world to another and (2) calculate their local location relative to other obstacles in order to follow safe driving rules, such as remaining centered and in the correct lane. Local localization algorithms are similar to indoor robotic algorithms, with the addition of road marking and road shape detection (Urmson et al., 2008), whereas global localization generally requires the use of GPS and IMU technology (and may even use infrastructure beacons or patterns) (Kaviani et al., 2016).

In (Levinson et al., 2007), global and local AV localization and mapping is established using GPS, IMU, wheel odometer, and LIDAR information to create an urban map with a resolution of five centimeters. The algorithm distinguishes between static and dynamic elements of the environment (for example, between the road and vehicles) and removes the dynamic elements from the map. This map can then be used for autonomous driving and localization and is an example of an *a priori* mapping strategy. This method was further improved by using additional probabilistic modelling in Levinson and Thrun (2010). Although both of these techniques are quite accurate, they require human-driven vehicles to pre-map the road and provide this information to the AVs prior to driving.

In other techniques, AVs map and localize while driving. This is known as Simultaneous Localization and Mapping (SLAM) (Dissanayake et al., 2001) and will be discussed further in Section 4.3.2. Stanford' s entry in the DARPA Urban Challenge used local road curvature, the reflectivity of the road and the vehicle' s inertial movement to increase the accuracy of GPS information, which was provided to the vehicle' s path-planning algorithm in real time (Montemerlo et al., 2008). Team MIT' s entry relied less on GPS information (using it only when absolutely necessary) and more heavily on local perception to provide data to the path-planning algorithm (Leonard et al., 2008).

4.3. Increasing the efficiency of localization and mapping

Since vehicles drive at much higher speeds than indoor robots, AVs require faster and more efficient algorithms. This is typically addressed through one of two methods: (1) by using pre-created, detailed and/or HD dynamic maps (leaving only localization to be completed during the autonomous driving) and (2) by selectively mapping certain areas of the road (similarly to how humans focus on the road in front of them).

4.3.1. A Priori and HD Mapping and Localization

Many state-of-the-art vehicles, such as the Google, Uber and Navya Arma vehicles, use *a priori* mapping methods (Boudette, 2017; Muoio, 2016; Navya, 2017). These methods consist of pre-driving specific roads and collecting detailed sensor data, such as 3D images and highly accurate GPS information. Large databases store the created detailed maps for vehicles to drive autonomously on those specific roads. Local localization is performed by observing similarities between the *a priori* maps and the current sensor data, whereas obstacle detection is achieved through observing discrepancies between the *a priori* maps and the current sensor data. This method is extremely effective for driving along roads that do not change often. However, as discussed previously, if drastic changes occur, the method may be unable to localize correctly or may detect harmless discrepancies, such as lighting or weather changes, as obstacles that need to be avoided.

In Ros et al. (2015), *a priori* mapping and localization is accomplished by combining the accuracy of offline perception with the real-time computation of online perception. The novelty of this method is that visual data is used for *a priori* mapping, whereas in most systems, active sensor data, such as LIDAR data, is used. This is advantageous, since with the expected increase in number of AVs on the road, active sensors may become unreliable due to the increased density of active sensor signals (Hischke, 1995). Alternatively, in Obst et al. (2012), localization was achieved by pre-creating 3D maps of tall surrounding buildings for raytracing purposes. This addresses the problem that vehicles cannot always obtain strong, reliable GPS signals in dense urban areas.

Google' s vehicles, which also use *a priori* mapping and localization methods, have autonomously driven over 2.4 million kilometers, including driving through complex situations such as intersections (Google, 2017). Despite these outstanding numbers, *a priori* methods such as these cannot handle many common situations. For instance, due to the limited number of distinct landmarks on bridges, Uber' s vehicles cannot localize themselves, and thus are unable to drive over bridges without human intervention (Muoio, 2016). Weather conditions, such as snow or fog, also create problems for this technique due to the drastic change in the environment' s appearance, making map matching difficult. Changes to the road, such as new construction zones, speed limits or traffic lights, also pose problems, as the vehicle assumes that major components of the environment will be identical to the original *a priori* data. Thus, a vehicle with an a priori-based localization and mapping may speed through construction zones or new traffic lights without noticing the change in traffic rules (Sorokanich, 2014). Furthermore, in order for this technique to be viable on a large scale, all roads around the world would have to be initially pre-mapped and then continually re-mapped in order for vehicles to adapt to new situations.

An emerging technique under the umbrella of *a priori* mapping and localization includes HD mapping. HD maps are based on *a priori* data; however, they are dynamic, updated in the cloud, and utilize V2I and V2V communication to improve accuracy. Essentially, HD maps provide centimeter-accurate *a priori* map information to AVs, and AVs provide the cloud-based HD maps with updated map information based on collected sensor data. The maps are continually updated in this manner offline (Seif and Hu, 2016). Although HD maps are not widely utilized today, initial prototypes have been implemented by Audi and BMW (Abuelsamid, 2017; Rabel, 2016; Seif and Hu, 2016). The main challenges with HD map technology regard the large size of the HD map data, latency in transmissions between the cloud and the AV, and the computational efficiency of the offline data processing (Seif and Hu, 2016). With improvements in these areas, HD maps could become the standard *a priori* mapping and localization technique for AVs.

4.3.2. Simultaneous localization and mapping (SLAM)

Vehicle localization performed while on the road (i.e., the localization portion of Simultaneous Localization and Mapping (SLAM)) does not rely heavily on *a priori* information. This allows AVs to continuously observe the environment and readily adapt to new situations. Consequently, localization through SLAM requires more computationally intensive algorithms and may be subject to more uncertainty depending on the sensors used and surroundings. These algorithms must differentiate between static objects in the environment (which can help with localization) and dynamic objects (which should not be used for localization, since they move) without any prior knowledge. Many of these algorithms currently rely on road marking detection for local localization, which pose problems when the road markings have faded, are partially occluded (by weather or other objects), or are non-existent (Gruyer et al., 2016a; Rebut et al., 2004; Wu and Ranganathan, 2013).

Various probabilistic techniques have been researched for discriminating between static and dynamic objects in the environment using SLAM-based methods. Early techniques include vehicles from the DARPA Urban Challenge. Carnegie Mellon University' s vehicle, Boss, differentiated between static and dynamic obstacles by flagging them as either "moving," "not-moving," or "observed moving," and then transferred these obstacles from a static map to a dynamic map and vice versa, allowing the vehicle to plan different routes based on obstacles' predicted motions (Urmson et al., 2008). An improvement on this method can be found in Cho et al. (2014), which includes detection and classification of vehicles, pedestrians, and cyclists.

Although Carnegie Mellon' s entry did not pre-map the Urban Challenge course (and thus can be considered to be using online, SLAM-based techniques), it relied heavily on *a priori* information, such as road shape and accurate road position (Urmson et al., 2007). Team MIT' s submission took a different approach, relying almost solely on currently perceived obstacles and road markings for localization. In their opinion, since human drivers do not require detailed, *a priori* maps or even GPS information, vehicles should not necessarily require this information either. Thus, similarly to a human, their vehicle gathered information about the environment while on the road to produce a local map, which was sent to a motion planner module (Leonard et al., 2008).

Other vehicles have used similar SLAM-based techniques. VisLab developed multiple AVs that relied on perception (such as camera vision) for local navigation and used sparsely detailed maps for global localization (Broggi et al., 2013). The vehicles semi-autonomously drove 13,000 km from Italy to China through various weather, road, and traffic conditions. In this challenge the vehicles did not plan global paths, but instead followed waypoints or platooned behind a human-driven vehicle in order to move from one point to another point on a map (Broggi et al., 2012), revealing a need for further research into real time SLAM-based methods. In Marais et al. (2014), image processing was completed while on the road to improve GPS accuracy. Instead of creating computationally heavy 3D maps, GPS accuracy was improved by determining where satellites were located (relative to buildings and the ego-vehicle) through image processing and excluding data from satellites that were hidden from view. However, the process was not as accurate as desired. Table 5 provides an overview of the localization and mapping methods used by prominent research vehicles.

When developing SLAM-based autonomous driving algorithms, it is important to consider current human driver behavior and ensure AVs can safely react to this behavior (Schnelle et al., 2016). The AV must be able to perceive and understand human drivers' intentions even when they are not "correct" or lawful (e.g., accidental lane departure (Wu et al., 2012) versus the intention to change lanes without signaling, which may be shown by a vehicle inching towards another lane) (Windridge et al., 2013). To address this difficulty, naturalistic driving studies (NDSs, in which driving behavior is observed and analyzed) have been performed, such as the 100-Car NDS (Neale et al., 2005). Although NDSs and human driving behavior are not the topic of this paper, the data collected through these studies may be used in multiple ways to address real time SLAM challenges and other autonomous driving challenges.

In Satzoda and Trivedi (2015), NDSs were analyzed to extract semantic and quantitative information from video, vehicle dynamics, global positioning, map, and orientation data. The data extracted included the vehicle' s position within the lane, which lane the vehicle was in, the vehicle' s speed, the road curvature, and the density of traffic. Although the intention of such extraction was to begin the automation of semantic analysis for crash prediction, the techniques used to extract such vehicle data may be used for SLAM-based vehicle localization.

In Janardhanan et al. (2015), researchers utilized similar lane marking detection techniques to localize while on the road and navigate through an experimental emergency scenario. In this article, the ego-vehicle determined its lane position as well as distances to various objects to plan and execute a safe maneuver around a vehicle parked partly in the ego-vehicle' s lane. Although the techniques used were effective, they were only used in a single scenario, in which there was only a single vehicle to avoid. In Wu and Ranganathan (2013), however, real time road marking detection was tested in more complicated scenarios. By determining the position and orientation of road markings in images collected from the ego-vehicle' s camera, the relative pose and position of the ego-vehicle within a lane could be determined. Nonetheless, the global position of this vehicle could not be determined without a highly detailed map of road marking locations (i.e., *a priori* information). Furthermore, the absolute error of the pose estimation was quite large, at 0.99 m (Wu and Ranganathan, 2013). A more recent method, described in Gruyer et al. (2016a), localized using road marking detection, road marking map, GPS, and INS/odometer sensor information and obtained highly accurate results; however, this approach also required *a priori* information.

In situations with multiple vehicles, V2V technology can optimize SLAM-based, lane-level localization. A Markov-based information sharing approach is used to communicate GPS data between vehicles, resulting in improved lane-level localization over single-GPS localization in Dao et al. (2006). However, it is noted in this article that there is still significant noise in the localization and further research in this area should continue.

The Tesla Model S is a well-known example of a semi-autonomous commercial vehicle that primarily uses real time SLAM-based techniques. The Tesla' s autopilot feature allows the vehicle to drive itself along freeways and highways, performing lane changes and autonomously adjusting its speed (under constant human supervision). However, the Tesla Model S cannot drive by itself through complex situations, such as intersections (Canada, 2017a) and still requires the human driver to take back control of the vehicle in unknown or unpredictable situations. This is a common theme throughout SLAM-based techniques. With further research into efficient perception data processing and situation-based high level decision-making, SLAM-based methods have the potential to be able to drive in all situations (not only pre-mapped situations), and furthermore, to overcome the challenges that a priori-based methods have been unable to address.

4.4. Recent emerging autonomous navigation approaches

Up to this point, it has been assumed that the autonomous navigation process includes the following stages: environmental perception, localization and mapping, path planning, decision-making, and vehicle control. However, some researchers are developing AV algorithms that skip the localization and mapping and path planning stages[1] and rely purely on environmental perception to make driving decisions. Thus, instead of the process depicted in Fig. 1, the process resembles Fig. 4 or Fig. 5. According to Chen et al. (2015), the navigation process could be streamlined by reducing the number of metrics (e.g., angle of the ego-vehicle, distance to obstacles, distance to adjacent vehicles, etc.) analyzed, allowing more computation time for environmental perception. Furthermore, without a local localization and mapping stage, the perception stage does not require the high level of detail and thus is less computationally expensive (Chen et al., 2015). To illustrate, instead of continuously detecting and classifying objects, the AV directly links a particular image or scenario with a driving action through machine learning techniques. This process is called the "behavior reflex approach" and is diametrically opposed to the "mediated perception approach", which is the standard method of AV perception that has been discussed in this paper (which includes perceiving and analyzing the environment, localizing the ego-vehicle, and planning detailed trajectories and maneuvers) (Chen et al., 2015). If the mediated perception approach falls out of favor, the requirements for the perception technology and as well as localization and mapping may change drastically. For example, the demand for vision-based perception may increase, and the demand for highly detailed *a priori* information may decrease.

[1] Note that the algorithms skip the local mapping and localization and path planning stages (i.e., creating detailed maps of the vehicle' s surroundings and planning detailed local paths to follow within this map). The global mapping and localization and path planning stages are still necessary for the vehicle to get from point A to point B; however, they can be computed prior to driving and are thus excluded from the navigation cycle.

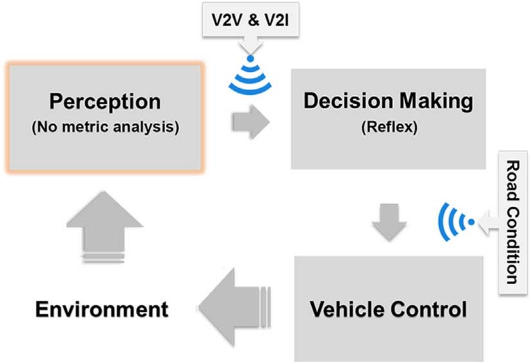

Fig. 4. Overview of the behavior reflex autonomous navigation process. Note that in the behavior reflex approach' s perception stage, no specific metrics (e.g., angle of the ego-vehicle, distance to obstacles, distance to adjacent vehicles, etc.) are analyzed.

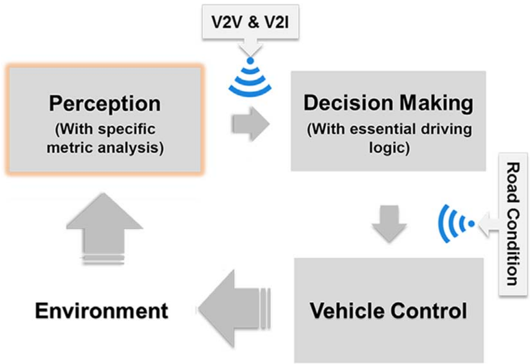

Fig. 5. Overview of the direct perception autonomous navigation process. Note that in the direct perception approach' s perception stage, specific metrics (e.g., angle of the ego-vehicle, distance to obstacles, distance to adjacent vehicles, etc.) are analyzed.

One of the first examples of an AV using the behavior reflex approach is the Autonomous Land Vehicle in a Neural Network (ALVINN) (Pomerleau, 1989). In this perception system, a neural network determines the vehicle' s trajectory based on images and laser range finder data. In a more recent example, a TORCS-simulated vehicle navigates a racetrack using the behavior reflex approach, demonstrating the approach' s ability to optimize acceleration and braking using only images as the input (Jan et al., 2013). Although the behavior reflex approach in these articles is much less computationally expensive than the widely-used mediated perception approach, the authors point out that it is not robust enough to drive through highly complex situations or complete complex maneuvers (Chen et al., 2015). As its name suggests, this approach is more of a "reflex" and is likely most useful when reacting to sudden events (e.g., collision avoidance or mitigation), but not for the development of high-level strategies or the prediction of hazardous situations (Chen et al., 2015). Thus, the authors propose the "direct perception approach," which combines data-gathering techniques found in the mediated approach with the computational efficiencies of the behavior reflex approach (Chen et al., 2015). Due to this increased computational efficiency, this approach could potentially address the problem of time and computation restraints of typical SLAM-based approaches in industry today.

In the direct perception approach, the vehicle completes sections of the mapping-related computation (for example, determining the vehicle' s current angle on the road and the distance to surrounding vehicles and lane markings) but does not create a complete local map or any detailed trajectory plans. Thus, this approach skips the majority of the localization and mapping stage and the entirety of the path planning stage. This process is depicted in Fig. 5. Using image data, relevant, specified local localization metrics (i.e., ego-vehicle angle, distances to road markings, and distances to nearby vehicles) and basic driving logic, the vehicle can directly make driving decisions.

In Chen et al. (2015), a TORCS-simulated AV successfully navigates a busy racetrack using the direct perception approach. This study uses deep neural networks and TORCS image data to determine the AV' s next steering angle and velocity. Furthermore, the same perception system was tested using video and images from the KITTI database, showing that the system could recognize lane configurations and transitions in the real world (Chen et al., 2015). Although this method shows promising initial results in terms of computational efficiency (i.e., does not parse entire driving scenes) and controlling the vehicle comparably to the mediated perception approach (Chen et al., 2015), it is unclear whether this method will be able to control the vehicle safely in real-world driving situations (e.g., less-structured or emergency situations).

Nonetheless, the direct perception approach developed in Chen et al. (2015) seems to have sparked great interest within the AV field. The direct perception approach is examined in Zhou (2016) to determine whether historical data has an effect on the approach' s future performance. By applying statistical methods, the researchers find that historical data in direct perception is, in fact, predictively useful. This provides grounds for testing more complex machine learning techniques with the direct perception approach (Zhou, 2016).

Furthermore, (Xiong et al., 2016) looks at combining a deep learning approach with a safety-based control approach to autonomous driving. This approach aims to develop a deep-learning driving technique with increased safety measures. As in Chen et al. (2015), the driving results are simulation-based and do not yet provide solid evidence for deep-learning-based approaches to be safe, efficient, and effective methods for real-world autonomous driving.

The direct perception, deep learning approach to autonomous driving provides an interesting alternative to classical AV techniques. Depending on the results of future research, this approach may change how AV perception is managed and achieved.

5. Future research areas and AV technology advancements

The previous sections in this article provided information about AV history, AV perception sensors, and AV localization and mapping while alluding to areas of research that need improvement. This section provides an in-depth summary of areas of AV perception requiring further improvement as well as information about recent related advancements in technology.

5.1. Automotive sensor research areas and advancements

This section provides a summary of future areas of research to improve AV sensors and information about recent advancements in AV sensors. The following list summarizes areas related to AV sensors needing further development:

- Improving detection and reducing uncertainty in poor lighting and weather conditions
- Improving detection and reducing uncertainty in complex environments
- Reducing uncertainty in sensor data by cross-verifying obstacle locations and signals through:
  - Further development of sensor fusion algorithms
  - Use of more sensors and sources for sensor fusion to build multiple layers of environment modeling
  - V2V and V2I communication
- Ensuring the public understands sensor capacity and limitations
- Using more passive sensors (versus active sensors) or developing effective algorithms to counteract the increased density and therefore interference of active sensor signals
- Decreasing the overall cost of AV sensor systems by:
  - Further developing sensor fusion algorithms using low-cost sensors
  - Utilizing new low-cost, highly-effective sensors that may be introduced in the near future (e.g., new LIDAR from Innoviz (Ackerman, 2016a))
- Developing fault detection and isolation systems for automotive sensors and algorithms
- Using multisensor data fusion in order to limit the impact of sensors' drawbacks and exploit the advantages of each sensor through using the sensors' complementarity and redundancy in order to improve accuracy, certainty, and reliability

As several key challenges remain unresolved for AV perception, many companies are competing for a piece of the AV technology market. Osram Opto Semiconductors just recently announced the development of a four channel LIDAR with a mass production price predicted to be less than fifty dollars (Howard, 2016). Another development in LIDAR technology includes low cost solid-state sensors, which are more resilient and smaller than conventional LIDAR (Ackerman, 2016b; Ross, 2017). Improvement to LIDAR technology such as this will help to reduce the price of autonomous features.

Additionally, Seegrid, a manufacturing robotics company, uses stereovision as the primary sensor for autonomous navigation (Pettitt, 2016). Even though vision is currently not the primary sensor used by companies such as Google and Ford (Amadeo, 2017; Center, 2016), many car manufacturers, including Audi, Mercedes-Benz, and Volvo, use the Mobileye sensor for their semi-autonomous features (Gitlin, 2016c). The Mobileye sensor primarily uses mono-cameras for obstacle detection and tracking, and road marking detection (Mobileye, 2017). Furthermore, a recent project involving primarily vision-based sensors includes the Transit IDEA Program. This system uses the Rosco/Mobileye Shield+ system to provide collision avoidance warnings to transit bus drivers (Spears et al., 2017). This system, as well as a second vision-primary system was tested in over 30 h of real-world driving with positive results, further contributing to vision-based AV perception research (Ke et al., 2017).

Tesla uses a similar concept (and used to utilize Mobileye technology (Lambert, 2017)) by integrating eight cameras, ultrasonic sensors and radar for their autonomous features (Canada, 2017b). As discussed, combining these sensor technologies will reduce shortcomings and provide necessary redundancy for autonomous driving. Taking a different approach, the company AutonomouStuff provides complete AV research and development platforms such as the Ford Fusion and Lincoln MKZ (AutonomousStuff, 2017). These platforms allow researchers to focus on the development of new algorithms to improve localization and mapping, path planning, high-level decision making and vehicle control instead of focusing on the sensor fusion framework required for these algorithms.

5.2. Localization and mapping research areas and advancements

In terms of localization and mapping, continued research to increase the reliability, efficiency and robustness of the algorithms is required before vehicles can reliably localize themselves in all driving situations. This may be completed by improving *a priori* based and/or SLAM-based localization and mapping methods. Additionally, it is expected that localization and mapping techniques will continually be updated as the improved automotive sensing techniques become available. Further research focused on improving *a priori* mapping and localization methods may include:

- Developing a system to compensate for the lack of large, interconnected, highly detailed databases that will be required for autonomous driving based on *a priori* maps, potentially through HD map technology
- Addressing poor localization in snow, rain and fog; in areas with fewer landmarks (such as on bridges or along long straight sections of roads); and along roads that have undergone large changes (such as construction sites) through:
  - Improved *a priori* information about such situations and landmarks, and/or
  - Improved SLAM through better sensing techniques and sensors
- Incorporating cooperative driving techniques (V2V and V2I) into localization and mapping to reduce uncertainty and improve vehicle safety (O'Brien et al., 2016)
- Developing a framework to ensure vehicles do not attempt to drive using outdated maps, and to address questions such as:
  - How old is too old for an *a priori* map?
  - Should vehicles legally be allowed to drive using an old map?
  - How will vehicles become aware of traffic pattern changes, such as construction zones?

SLAM-based methods also must be improved in terms of efficiency, accuracy, reliability, and robustness for complex situations. Further research to improve localization and mapping in real time may include:

- Improving the efficiency of local localization and mapping algorithms to be used in real time (and not analyzed after the fact, as in Satzoda and Trivedi (2015))
- Improving the robustness of SLAM in poor weather conditions
- Enhancing GPS reliability and accuracy, or reducing the cost of DGPS technology
- Utilizing further V2V and V2I communication to reduce localization uncertainty

Although the DARPA Urban Challenge attempted to address problems with a priori-based localization by preventing the entrants from pre-mapping road sections, the vehicles that placed first and second still relied heavily on *a priori* information, such as generic road structure and road markings. Furthermore, the entries that did not rely heavily on *a priori* information also did not compete in complex situations, such as urban areas with pedestrians and cyclists. Other vehicles that localize through SLAM have partially addressed such situations, including the Tesla, but still lack the ability to autonomously drive through any situation other than straightforward highway/freeway driving.

Determining a proper balance between relying on *a priori* information to increase algorithm efficiency and current perception data to increase the vehicle' s ability to adapt to new situations remains an unresolved challenge in AV research. Certain aspects of *a priori* data have proven to be necessary, such as address coordinates, whereas other *a priori* data is useful, but unnecessary, such as road shape or detailed, pre-mapped 3D images. Future AVs will need to rely on a combination of current perception data and *a priori* information; however, it is clear that further research and development is required to provide reliable, accurate, and robust enough perception algorithms for full autonomy. In fact, perception stages remain essential to guaranteeing the development of efficient, fully automated applications.

Furthermore, in recent works the direct perception approach and other deep learning driving techniques have been proposed to improve performance (without relying on *a priori* information) by streamlining the autonomous navigation process by eliminating the localization and mapping and path planning stages or using end-to-end deep learning techniques (Chen et al., 2015; Bojarski et al., 2016). However, further research must be completed concerning how the direct perception approach handles real-world emergencies. This is especially pertinent since the primary purpose of AVs is to increase safety by decreasing human-related error.

Although sensor technologies allow AVs to outperform human perception in many areas, AVs are not yet ready to provide level five autonomy. With the aforementioned improvements, however, AVs will be much closer to providing the efficiency, mobility, and safety benefits predicted.

6. Conclusions

In this paper, an overview of AV sensor technology, localization and mapping techniques, and future perception research areas were presented. Although current perception systems implemented in Level 1 to Level 3 autonomous systems have been shown to increase vehicle safety, there is still much to improve upon before fully autonomous vehicles will be available to the public. The three main areas requiring improvement presented in this paper include: (1) reduction of uncertainty in perception, (2) reduction in cost of perception systems, and (3) operating safety for sensors and algorithms. A fourth area not discussed in this paper, but that is of equal importance, includes the efficiency of computational methods and algorithms for AV perception. These methods comprise a large amount of research conducted in the AV field. Researchers are continually aiming to improve the efficiency of detection and classification, localization and mapping, and other AV perception related algorithms (Huang et al., 2017; Jagannathan et al., 2017). All in all, with further research and development of AV perception systems, AVs will likely be driving on public roads while increasing driving safety, sustainability and mobility in the near future.

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