

# Autonomous Driving: A Survey of Technological Gaps Using Google Scholar and Web of Science Trend Analysis

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**Abstract**—Autonomous Driving (AD) introduces dramatic changes to the way we travel. This emerging technology has the potential to impact the transportation sector across a wide array of categories including safety, efficiency, congestion, legislation, and travel behavior. In this survey, we review the main issues involved in AD as discussed in the literature, and shed light on topics that we consider requiring further development based on Google Scholar and the Web of Science (WoS) data base. The paper also provides the results of research trends related to Autonomous Driving based on analysis of the number of search results listed in google trends. According to our research, the fields of Vehicle-to-Vehicle (V2V) and Vehicle-to-Cloud (V2C) networking are of higher interest due to the technological gaps and standardization processes. In addition, cyber and security research is in acceleration due to its importance.

**Index Terms**—Autonomous vehicle, autonomous driving, V2X, safety, cooperative driving, Google trends.

## I. INTRODUCTION

**A**UTONOMOUS driving requires a combination of many capabilities, among them: localization, motion planning, vehicle systems control (steering, acceleration/deceleration, signaling, etc.), road perception, intention prediction of other road users, awareness of dangers, human factors etc. The level of importance for each capability varies according to the level of driving automation. In this paper we differentiate between the terms “Autonomous Vehicles (AV)” and “Autonomous Driving (AD)”, where AD is a wider term that incorporates AV as well as other technologies such as traffic behavior, human-vehicle interaction, pedestrians etc.

Even though the first experimental AV was revealed in 1926 [1], the first modern AV was presented in 1986 by a team from Carnegie Mellon University [2]. Since 2010, many major automotive manufacturers such as GM, Mercedes Benz, Ford and Toyota, have been developing AVs [3]. In 2013, Toyota demonstrated an AV equipped with numerous sensors and communication systems [4]. In 2016, Google’s AV passed

Manuscript received 9 September 2021; revised 21 November 2021 and 15 March 2022; accepted 28 April 2022. Date of publication 11 May 2022; date of current version 7 November 2022. The Associate Editor for this article was K. Yi. (Corresponding author: Shlomi Hacohen.)

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Digital Object Identifier 10.1109/TITS.2022.3172442

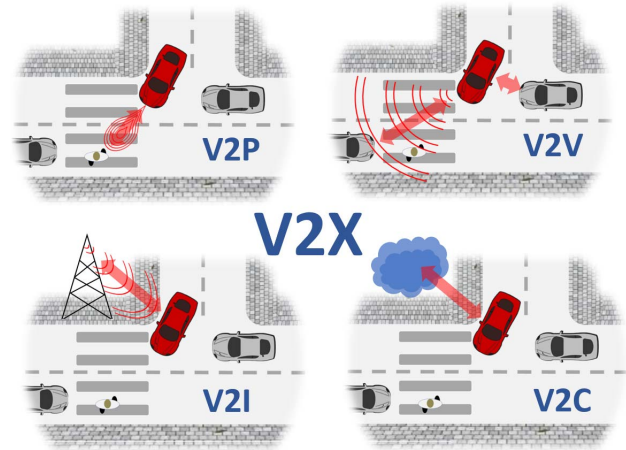


Fig. 1. Vehicle to pedestrian (V2P), Vehicle to Vehicle (V2V), Vehicle to Infrastructure (V2I) and Vehicle to Cloud (V2C) architectures.

the significant milestone of travelling over one million kilometers. These events present a glimpse of the landmarks in AV development that, due to the complexity of the task, progresses slowly with a considerable amount of attention to safety and reliability.

The large amount of data needed by AVs for a reliable decision making comes from a variety of onboard sensors and algorithms that perform data fusion and estimation, and from external sources like other AVs (V2V), environmental and infrastructure devices (I2V), cloud data bases (C2V) and any combination of these (X2V). Fig. 1 illustrates schematically some AV data transfer architectures. In the Society of Automotive Engineers’ (SAE) definitions of automation level, “driving mode” means “a type of driving scenario with characteristic dynamic driving task requirements (e.g., expressway merging, high speed cruising, low speed traffic jam, closed-campus operations, etc.)” [5].

As a result of the popularity of AV research, many surveys that review technologies involved with AVs were published in recent years. These include perception [6]–[8], vehicle-control [9]–[11] localization [12]–[15], cooperative driving [16]–[19], machine-learning [20]–[22], racing AVs [23] and cyber protection [24]. This survey is different from previous surveys in two main aspects: first, it provides a wide field of view of many research areas rather than focusing on a

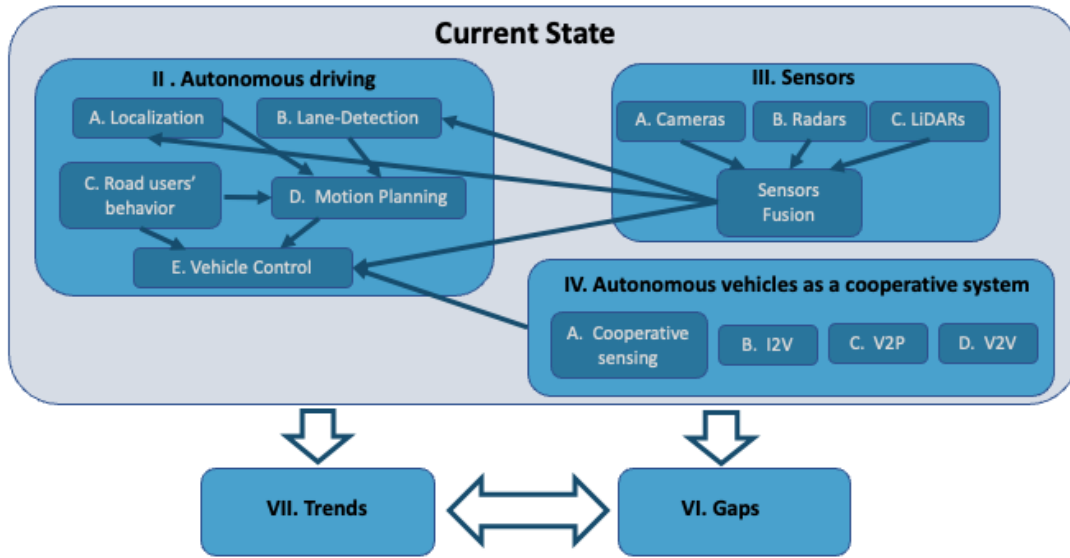


Fig. 2. A flowchart of the paper.

single subject. Second, it discusses the gaps between the current and the required stages that will enable everyday usage of AD.

Autonomous driving is expected to provide beneficial changes to the way we travel, which will impact aspects such as safety, efficiency, congestion, and travel behavior. Crash avoidance, travel time reduction, fuel efficiency and parking solutions are expected to save thousands of dollars per year per AV [25]. However, the implementation and mass market penetration of AVs will most likely take time, as current costs are unaffordable for the common user, there are still a few technological barriers, and the human aspects, infrastructure and legislation are lagging far behind.

The aims of this paper are to provide a wide review of the main issues involved in AD as discussed in the literature, and to shed light on topics that require further development. We do so by, first, presenting the main topics involved with autonomous driving. We then point out the main research gaps using an analysis based on the number of search results listed in Google Scholar and Web of Science data bases.

The flow chart shown in Fig. 2 depicts the organization of the paper. In section II we review the current technologies and methods used in AD. In particular, we review the common technologies related to localization and lane detection of AVs, and the models of road users' behavior. These technologies and models affect motion planning of AVs (section II-D) which is performed by the AV's control system (section II-E). Section III provides an overview of the common sensor systems for AVs and their data fusion which also affect the vehicle motion planning and control. In section IV we discuss the concept of AD in terms of multiagent systems as it becomes a critical notion in AD. Section V discusses the current technological gaps which need to be addressed before AD takes over common driving, and section VI provides the recent trends in AD research and development, based on Google Scholar search results looking at the annual results for key

terms. These results are used as indicators for the trends in AVs and AD. Finally, section VII provides a discussion and a summary.

## II. AUTONOMOUS DRIVING

The concept of AVs is based on replacing the driver with an autonomous system that can control the vehicle on traditional existing roads, together with other road users. The SAE defined five automation levels of AD, described in Table I. Since the overall aim of AD is to eventually replace the driver, several features must be adjusted and integrated in order to achieve safe and reliable travel. According to [26], AD comprises three layers:

- 1) The perception layer, that perceives the critical environmental settings in the vicinity of the vehicle, e.g., lane tracking, obstacles, road signs etc.
- 2) The reference generation layer, that provides the reference instructions, i.e., the required path planning and obstacle avoidance maneuvers based on inputs from the perception layer.
- 3) The control layer, that performs the required tasks that guarantee the trajectory tracking performance, expressed in terms of steering maneuvers (usually performed by the front axle) and acceleration/braking maneuvers. In the following sub-sections, we discuss some of these fundamental features.

### A. Localization

The localization of AVs is an essential task that is fundamental to path planning and safety. Although localization schemes are well discussed in the literature, these may not address all AD challenges such as data fusion, environment dynamics etc. Since Global Navigation Satellite System (GNSS) data is often not suffice for localization, other sensors are used in order to improve the localization accuracy. This obviously increases the localization calculation

TABLE I  
AV LEVELS OF AUTOMATION (ACCORDING TO SAE) [27]

Automation Level	Definition
0 No automation	All driving aspects are performed by the human driver
1 Driver assistance (hands-on)	Performance shared by the automation system and the human driver
2 Partial automation (hands-off)	All driving aspects are automated, yet, the human driver supervises the automation system.
3 Conditional automation (eyes-off)	All driving aspects are automated, yet, may request the human driver to intervene.
4 High automation (mind-off)	As for Conditional Automation, however the automatic system continues control even if the human driver does not respond to a request to intervene.
5 Full automation (steering wheel optional)	Human intervention never requested.

complexity. Researchers claim that AV localization requires further development to reduce the calculation time, increase Global Position System (GPS) accuracy, and to test other types of sensor fusion [12], [28]. Consequently, researchers and commercial companies are developing new localization methods to face this challenge. Motion planning for AVs must also consider the estimation error associated with localization methods. Wong *et al.* [29] present a method to estimate the localization error based on 2D geographic information alone. They estimate the localization error with 87.4% of predictions within less than 5cm error.

Many research papers and patents present improvements to the localization of AVs using passive images [30]–[32]. Such sensors are low-cost and, together with smart image processing, they achieve high accuracy. These methods use visual observations applied by on-board cameras to improve the localization accepted from GNSS.

In recent years, the use of LiDAR (Light Detection and Ranging) sensors became more common in AV applications, especially for collision avoidance. As a result, LiDARs are often the favored sensor for map-based localization since they have high resolution and high accuracy. Wang *et al.* [33] presented a three-step method for map-based localization using LiDAR measurements. First, the point cloud of a single frame is used for curb detection. Then, a contour line of these points is conducted. The last step is the matching between the map and the contour lines. Mukhtar *et al.* [34] used sparse 3D LiDAR scan data for map-based localization in order to reduce the sensor cost.

As mentioned above, the control of AVs relies on data from multiple sources, including Inertial Measurement Unit (IMU), wheel odometry measurements, GPS, GNSS, LiDAR, RADAR and cameras. As a result, methods for data fusion for localization are very common. For example, DeBitetto *et al.* [35] used inertial sensors as well as RADAR data to improve GPS localization of AVs. Yu *et al.* [36] presented a localization scheme for AVs in an urban area. They used a prior point cloud of the environment, but since the environment changes frequently, this prior data may be irrelevant. The authors developed a novel data fusion algorithm that estimates the reliability of each point from the prior map based on the new observations.

Due to the complexity of analyzing data from multiple sensors, researchers often prefer the use of machine-learning and neural-networks [36]. In [37], researchers investigated a map of nodes and edges they call the *hybrid-map* which enables the implementation of different types of machine-learning methods. The authors demonstrated this concept in an AV equipped with two LiDARs providing data input, however the authors state that this method needs further verification and improvement to ensure a robust system.

### B. Lane-Detection

One of the most important elements of AD and Advanced Driver Assistant Systems (ADAS) is lane-detection. This feature commonly uses computer vision algorithms in order to identify the road's edge-markings and lane-marking in images taken by cameras. The vehicle and the lane relative position is then calculated. ADAS will alert in case the vehicle's position in the lane is not safe, while the AV uses this information for keeping the car in lane using autonomous steering. Similar to Automatic Emergency Braking (AEB), the Automated Lane Keeping System, known as ALKS, is also becoming a standard feature in new vehicle models following automation level 3 of the SAE. The ALKS takes control over steering in order to reduce the probability of a collision due to unsafe lane changes. The ALKS mechanism is integrated in the vehicle's design such that it can override a driver's maneuvering of the steering wheel. In 2021, 42 countries approved the adoption of an internationally valid regulation for ALKS. Currently ALKS is limited to passenger vehicles driving up to 60km/h and carrying up to 9 passengers. Lack of clarity in lane markings, poor visibility due to bad weather, illumination and light reflection, shadows, and dense road-based instructions can contribute to lane detection failures. Most lane detection methods are based on analyzing 2-D images captured from a camera (usually mounted behind the front windshield). These vision-based approaches can be categorized into two methods: feature-based and model-based. The model-based methods commonly use a mathematical model with the relevant parameters to describe the lane structure [38], [39]. For example, researchers in [40] presented real-time lane marker detection in urban streets. Their method generates a top view of the road, uses Random

Sample Consensus (RANSAC) line fitting for the straight lines, and a fast RANSAC algorithm for Bézier Splines fitting. The feature-based method, though known for its robustness against noise, is difficult to implement since it requires some prior-known geometric parameters and heavy computation. The feature-based methods analyze images and detect the gradients of pixel information or the color of patterns to recognize the lane markings. For example, the researchers in [41] presented a robust and real-time vision-based lane detection algorithm by reducing the image to an efficient Region of Interest (RoI) in order to reduce the high noise level and the calculation time. Their method also removes any false lane markings and tracks the real lane markings using the accumulated statistical data. Their experimental results show that the algorithm gives accurate information and fulfills the real-time operation requirement on embedded systems with relatively low computing power. For more examples see: [42]–[46].

### C. Non-Automated Road Users Behavior

One of the biggest challenges in AD is to predict the motion of non-automated road users, e.g., human-driven vehicles, pedestrians, cyclists and pets as it involves unknown and stochastic variables. Twaddle *et al.* [47] focused on the increasing need for bicycle behavior models in urban areas. Yao *et al.* [48] proposed a behavior model for conflicts in a mixed vehicles-bicycles scenarios. Li *et al.* [49] proposed a *cellular automaton* model that analyzes the behavioral characteristics of bicycles' illegal lane-changing behavior. Recent research dealing with AD and pedestrian safety explored the potentials and limitations of pedestrian detection [50]. The research analyzed nearly 5,000 Video records of pedestrian fatalities in 2015 in the Fatality Analysis Reporting System, and virtually reconstructed them under a hypothetical scenario that replaces the vehicles involved with AVs equipped with state-of-the-art technologies. They concluded that although technologies are being developed to successfully detect pedestrians in order to prevent fatal collisions, the current costs and operating conditions substantially decrease the potential for reducing pedestrian fatalities in the short term.

The behaviour of humans as crowds (see [51], [52]) differs from that of pedestrians crossing a busy road. The high heterogeneity between pedestrians and vehicles in terms of maneuverability, speeds, field-of-view etc. makes the prediction of an individual pedestrian's behaviour much more complicated than that of a crowd's behavior. Crowds are typically considered as homogeneous individuals and the high density enables to assume continuous interactions between them ([53]). Therefore, the prediction of pedestrian behavior requires deeper understanding of both pedestrian and driver behavior. Since psychological considerations are convoluted with the trajectories planned by individual pedestrians, research on pedestrian attitudes may have great impact on the behavioral models. For example, Zhou *et al.* [54] used structural equation modeling to predict pedestrian crossing behavior. The authors presented a questionnaire with a scenario involving the violation of

road-crossing rules and asked participants about their attitude towards such violations. Ye *et al.* [55] studied pedestrian behavior where road-crossing is done in groups, by using a behavioral model-based simulation. They analyzed the interactions between groups of pedestrians and vehicles at unsignalized intersections. In particular, they examined the mid-block crossing, which is characterized by a long straight road that enables vehicles to move at high speed, making it difficult to judge the speed of oncoming vehicles. Pawar *et al.* [56] analyzed and evaluated the dilemma-zone (an area located before the road crossing) for crossing pedestrians at mid-block crossings.

Several researchers developed pedestrian models that consider local behavior of the individual pedestrian. Hoogendoorn and Bovy [57] considered pedestrians as autonomous controllers, which minimize a cost function while moving toward a target destination. Blue and Adler [58] showed that a simple set of rules can effectively describe pedestrians' behaviors at the micro level. They modeled bi-directional pedestrian motion using a Cellular Automata micro-simulation to confirm this claim.

Pedestrian road-crossing models involve a number of factors. Duives *et al.* [59] evaluated pedestrian behavior models by considering eight distinct motion-based cases and six phenomena of crowd movement. The researchers showed that models of pedestrians crossing must fit the specific scenario. Even though pedestrians share the same motivation, i.e., crossing the road safer and faster, each pedestrian has his/her own target location and level of urgency, while possessing varying physical capabilities [53], [60], [61]. Guo *et al.* [62] confirmed that the behavior of road-crossing pedestrians depends mainly on the waiting time. Hacoheh *et al.* [63] presented a statistical algorithm for estimating the pedestrian's trajectory while crossing busy roads. Their behavioral model depends on the pedestrian's level of urgency alone.

Due to the complexity of such predictions, researchers focus on specific interactions between pedestrians and vehicles. Hashimoto *et al.* [64] developed a particle filter-based model of pedestrian behavior. The authors focused on the scenario of left-turning vehicles at signalized intersections when crossing at signalized crosswalks. Wang *et al.* [65] developed a pedestrian model for scenarios of mid-block crosswalks and intersections. Lee and Lam [66] presented a model which estimates the walking speed of pedestrians at crowded crosswalks, and Bonnin *et al.* [67] considered especially the zebra-crossings case.

An innovative strategy for developing pedestrian models implements common robotic motion planning algorithms to predict the trajectory of pedestrians. Such methods refer to the vehicles as dynamic obstacles that should be avoided, and the target is the other side of the crosswalk. Zeng *et al.* [68] implemented artificial-potential-field algorithm. Hacoheh *et al.* [69] use *Probability-Navigation-Function* to predict phenomenon of pedestrian crossings. In their research, the paradox of risk aversion was explored by simulating the pedestrians behavior while crossing the road when vehicles are approaching. Xiao *et al.* [70] introduced a Voronoi diagram-based algorithm for a pedestrian flow model,

and Waizman *et al.* [71] developed their method based on *Velocity-Obstacle*.

#### D. Motion Planning

The path planning task for AVs has been intensively researched over recent decades. It is common to divide the path planning problem into global and local planning. The planning techniques can be classified as (i) Graph search algorithms, such as Dijkstra [72]–[75] or A-star [76]–[79], which assume a set of known configurations with the goal of finding the path from two configurations passing through the known configuration set; (ii) Sampling based planners, such as RRT (Rapidly-exploring Random Trees) [80]–[83] that simplify the approach of grid sampling of the configuration space by sampling the region of interest with the desired density. Interpolating curve planners are used to smooth the paths given by the path planners. An Artificial Potential Field (APF) [84] or Navigation function (NF) [85] also perform well for AD [86]–[89].

Fully automated driving functionality also requires a reliable environment mapping, used in the AVs' control schemes. Brown *et al.* [90] introduced a control framework that integrates local path planning together with path tracking using model-predictive-control. The controller first plans a trajectory that considers the vehicle state (position and velocity) and the desired path. Then, two safe envelopes are considered: one for stability and the other for obstacle avoidance. Moriwaki [91] presented an optimal steering control method for electric AV based on  $H^\infty$  that aims to follow a chosen trajectory while keeping a certain stability margin. da Silva and de Sousa [92] used dynamic programming for AV motion control, where the objective is to follow a desired path while keeping the shortest distance between the vehicle and the desired path under some predefined threshold. Kessler *et al.* [93] introduced two novel approaches for extracting a topological road-graph with possible intersection options from sensor data, along with a geometric representation of the available maneuvering space. Also, a search and optimization-based path planning method for guiding the vehicle along a selected track in the road-graph and within the free-space is presented. They compared the methods by simulation and showed results of a test drive with a research vehicle. Their evaluations show the applicability in low-speed maneuvering scenarios and the stability of the algorithms even for low quality input data. For more methods of trajectory tracking and path following, see [94]–[96].

The field of motion planning which simultaneously considers safety and human comfort is yet to be fully developed. Magdici and Althoff [97] presented a fail-safe motion planner for AVs, which simultaneously guarantees safety and comfort by combining an optimal trajectory with an emergency maneuver. Solea and Nunes [98] presented a path-following control system together with a smooth velocity planning, including parameters to ensure the comfort of the human body. An important field of study is the passengers' feeling of safety in an automated vehicle which immerses when driving in urban environments, where the path must be smoothed in the planning stage before the trajectory tracking task.

The researchers in [99] implemented 4th and 5th degree Bézier curves in their path planning generation. They focused on urban scenarios (intersections, roundabouts, and lane changing) and speed planning for comfortable, safe motion.

Since AVs act in environments that involve humans, motion planning must also involve the consideration of ethical issues. For example, decision making in cases of inevitable accident or right of way. The authors in [100], [101] discuss the decision making of AVs from an ethical point of view.

The use of *Machine-Learning* (ML) seems to be an attractive method for AVs perception and motion planning (see for example [102], [103]). In [104] the authors presented a neural network model to analyze the data captured by the sensors. Then, a decision-making system calculates the most suitable control signal for the vehicle based on the observations. Isele *et al.* [105] solved AVs' intersection problems by utilizing Deep Reinforcement Learning which enables safe manoeuvres in the case of sensors' occlusions.

The complexity heterogeneity of scenarios of road driving make motion planning a challenging task. Banerjee *et al.* [106] investigated all disengagement and accident reports obtained from The California Department of Motor Vehicle (DMV) databases between 2014-2017, and found that ML-based systems are the primary cause of 64% of all misjudgment. Koopman and Wagner [107] stated in their paper that "...there does not seem to be a way to make ultra-dependable levels of guarantees as to how a ML system will behave when it encounters data not in the training set nor test data set". Researchers address this challenge by applying additional algorithms to block unsafe maneuvers. Mirchevska *et al.* [108] used Reinforcement Learning for lane changing of AVs. They addressed the uncertainty issues by combining ML with safety validations to ensure that only safe actions are taken.

#### E. Autonomous Vehicle Control

Autonomous driving requires a control system that guarantees a safe performance even in extreme scenarios such as heavy traffic, unexpected behavior of other road users, and poor visibility. As mentioned, vehicle control (manual or autonomous) can be divided into two major tasks: steering and accelerating/decelerating. All other tasks related to safe driving, for example tracking, path planning, and obstacle avoidance are based on these two fundamental capabilities. The initial theoretical and experimental studies on robotic systems and driving models were developed in the 1950s and 1960s, (e.g., [109], [110]). These studies aimed to improve driving safety by eliminating the negative outcomes of human errors in controlling vehicles by implementing highly reliable automatic control systems with faster and more consistent reactions. In particular, these studies focused on headway safety policy, longitudinal and lateral control of individual vehicles, and highway systems operations. These early systems used inductive cables and magnetic markers embedded in roadways to determine a vehicle's location. Shoval *et al.* [111] presented a robot driver system that controlled passenger vehicles and trucks in a vehicle manufacturer's Automatic

Durability Road (ADR) test facility. The robot was installed on the driver seat and mimicked the actions of a human driver, manipulating the vehicle's steering wheel, acceleration and brake pedals, and gear stick. The installation of the robot on the vehicle required 4 hours and did not involve any intervention in the vehicle's mechanisms. The lateral position of the vehicle was determined by electric wires embedded in the center of the driving lanes, where each wire was characterized by a unique frequency. Two inductive coils were connected to the front bumper of the vehicle and measured the electromagnetic signals from the electric wire. The difference between the signals from the two coils indicated the lateral position of the vehicle relative to the electric wire. Steering commands guided the vehicle along the required lane based on the coils' data. The longitudinal position was determined by a set of low frequency FM transponders embedded along the lane next to the guide wire. The transponders (TIRIS – Texas Instrument Registration and Identification System) were positioned a few meters apart along the track, providing reliable and accurate data on the vehicle's absolute longitudinal position. The DARPA Grand Challenge (DGC), initially introduced in summer 2002, was one of the most important milestones in the development of autonomous road vehicles. The first challenge included 17 teams attempting to complete the 140-mile course from Barstow, California to Primm, Nevada. Although the winning vehicle traveled only 7 miles (5% percent of the planned route), the DGC was a great success. Subsequent challenges included a route from Los Angeles to Las Vegas (380 km), limited to 10 hours without any human intervention (won by STANLEY team [112]), and the 2007 DARPA Urban Challenge, where vehicles were required to drive in traffic, and to perform complex maneuvers such as merging into traffic, overtaking other vehicles, parking, and crossing intersections [76]. The DARPA Urban Challenge was a ground-breaking event as the vehicles were required to negotiate other manned and unmanned vehicles in a close-to-real urban environment. Following the DARPA challenge, various technologies were developed and implemented for the control of unmanned vehicles. These technologies enabled steering and speed control as well as implementing some of the features in human-driven vehicles. For example, Automatic Emergency Braking (AEB), also known as Advanced Braking Systems, is now a standard technology in many modern passenger vehicles [113]. This technology can slow down and even stop a vehicle autonomously when it detects that the driver fails to respond to traffic events that may lead to an accident. Many countries around the world are enforcing or planning to enforce the implementation of AEB systems in new passenger, SUVs and light commercial vehicles. Automakers in the United States committed to include AEB as a standard feature on all new vehicle models starting in 2022.

Summing up, the ability to control the vehicle's steering and speed is the core of the AV functionality and many modern Advanced Driver Assistant Systems (ADAS) make use of it. Some gaps still remain such as additional criteria for optimizing the vehicle control and the user experience, and improving the vehicle Mean Time Between Failures

### III. SENSORS

One of the first works on sensor systems for AVs was presented by Waxman, [114] where a camera was used for the control of the vehicle. The hardware at this time was inefficient as the frame-rate was too low for the controller. The researchers maintained continuous motion by what they called 'looking ahead' and then 'driving blind' for a short distance until the camera took the next frame. The use of cameras as a control input in AVs gained momentum at the early 1990's. [115] used an improved processor to control the vehicle. The vision system estimated the lateral position and deviation of the vehicle relative to the white lines in the frame. Currently, all systems dealing with AVs use data-fusion techniques. This enables an overlap of data in the region of interest ([116]).

#### A. Camera Sensors

In recent years, cameras became the most common modality sensor due to their high information content, lower cost and operating power, and the ability to use ultra-sonic or radar as auxiliary sensors if necessary. AVs are generally equipped with video cameras in order to "see" and interpret the objects in the road. Multiple onboard cameras allow vehicles to maintain a 360° view of their external environment, thereby providing a broader picture of the traffic conditions.

Today, 3D cameras are utilized for displaying highly detailed and realistic images. Computer vision algorithms (such as OpenCV) can automatically detect objects, classify them, and determine their distance to the vehicle. For example, 3D cameras can easily identify other vehicles, pedestrians, cyclists, traffic signs and signals, road markings, bridges, and guardrails. Note that poor weather conditions such as rain, fog, or snow can prevent these cameras from clearly detecting obstacles in the roadway. Additionally, in situations where the colors of the objects are similar or lack contrast to the background, the detection algorithms may fail [117], [118].

One of the most known features for object detection is the Histogram of oriented Gradients (HoG) [119]. When calculating the HoG feature, the image is divided into small cells, and a histogram of gradient directions is compiled for the pixels within each cell. This approach may also be used for human detection [120].

The Convolutional Neural Network (CNN) approach enables features' extraction by integrating the features' labels (bounding boxes) into the learning process, and all features are automatically learned from the training data [121]. CNN is commonly used for human detection (see e.g. [122]) and is further improved to R-CNN and YOLO [123], [124] which requires a reduced computational cost and therefore is suitable for real-time operation.

There are many examples where cameras are the main or exclusive sensor. Heng *et al.* [125] presented the AutoVision project, which aims to develop localization and 3D scene perception capabilities for AVs based on vision sensors only. Kuramoto *et al.* [126] developed a scheme for computing 3D positions of distant vehicles based on mono-camera observations. The accuracy of the vehicle's maneuvers estimation may

be improved by using onboard monocular camera together with other odometry sensors [127]. For example, a monocular camera may also be used for localization by tracking known street markers. Lu *et al.* [128] utilized road markings as landmarks. Using the vehicle's odometry and epipolar geometry constraints, they were able to estimate the vehicle's position and orientation.

Stereo vision can be used with less preliminary knowledge. In this technique, the length of the objects may be unknown. An example of stereo vision for a 3D vision reconstruction was presented by Kemsaram *et al.* [129], who used three deep neural networks simultaneously to perform free-space detection, as well as lane boundary detection and object detection on image frames captured using AV's stereo cameras.

### B. Radar Sensors

Onboard radar (Radio Detection and Ranging) sensors send out radio waves that detect objects and gauge their distance and velocity in relation to the vehicle in real time [130]. Radar is a key technology for AVs and ADAS due to its robustness to environmental variations such as inclement weather (fog, rain, etc.) and lighting conditions, and their long-range detection [131].

Radar sensors may be divided into two groups: Short range sensors (24 GHz) are usually used for blind spot monitoring, lane-keeping and parking assistance. Long-range sensors (77 GHz) are used for maintaining safe distance and brake assistance [132]. Radar sensors may also be used for identifying vulnerable road users. Stolz *et al.* [133] investigated the use of radar sensors to identify cyclists in AEB systems. Nabati and Qi [134] proposed the RRPN (Radar Region Proposal Network) algorithm for object detection. Based on the radar observations, objects are mapped to the image coordinates.

The impact of occlusion, antenna beam elevation angle, linear vehicle movement, pedestrian motion, and other factors are investigated and discussed in [135]. Their experiments show that although over 95% of pedestrians can be correctly detected in optimal conditions, under real life conditions, recognition of pedestrian motion by radar only is insufficient due to insufficient Doppler frequency and spatial resolution, as well as antenna side lobe effects. An emerging research work that deals with dual function radar-communications device is presented in [136].

### C. LiDAR Sensors

LiDAR technology is currently the most common technology capable of delivering accurate real time 3D data due to the use of a laser-based point cloud. Real-time LiDAR sensor technology is used in a variety of commercial applications including AVs, vehicle safety systems, 3D aerial mapping and security. Though the benefits of 3D point-cloud data are clear, most AVs require multiple LiDAR sensors which make the AV's sensor system expensive [137].

LiDAR sensors create 3D images of detected objects and map the environment. Moreover, LiDAR can be configured to create a full 360-degree map around the vehicle rather than relying on a narrow field of view as compared to radar sensors.

Because of these two advantages, AV manufacturers and users such as Google, Uber, and Toyota, incorporate LiDAR systems in their sensors suit. For research on LiDAR and pedestrian recognition by AI see [138], [139].

LiDAR–radar sensor fusion is more robust to environmental changes than cameras since it uses a synergy laser and radio frequency signals (see [140]–[143]). For example, Kwon *et al.* [144] proposed a new detection scheme for occluded pedestrian detection by means of LiDAR–radar sensor fusion. The object within the occlusion region of interest is detected by the radar measurement information, and the occluded object is estimated as a pedestrian based on impulses in the Doppler observations.

As of 2022, LiDAR sensors are much more expensive than radar sensors. The LiDAR systems required for AD can cost well above 10,000\$ per unit, while the top sensors, currently used by Google and Uber, costs up to 80,000\$. In addition, bad weather conditions such as snow or fog may block the LiDAR sensors and affect their ability to reliably detect objects in the road. In [145] the researchers overcome the LiDAR's cones problem, which appears when objects block the LiDAR's beams and make the point-cloud perforated, by using a stereoscopic camera system. Neural networks adapt the camera's observations to convert them to pseudo-LiDAR representations — essentially mimicking the LiDAR signal.

## IV. AUTONOMOUS DRIVING AS A COOPERATIVE SYSTEM

Traditionally, the term Autonomous Driving refers to the technology that enables automatic operation of a single vehicle's control functions (steering, throttle, braking, etc.). As such, the vehicle may be equipped with all the actuators and sensors that are needed for the loop-closure. A different approach is the concept of *multi-agent-systems* or *cooperative AVs*, where the control of each vehicle, in addition to the environment conditions, is related to the operations of all other AVs in the vicinity [146].

Individual vehicles may benefit from information obtained from other vehicles in the vicinity, especially information related to traffic congestion and safety hazards. Vehicular communication systems use vehicles and roads infrastructure units as communicating nodes in a peer-to-peer network, providing each other with information. Vehicular communication systems raise the efficiency of all cooperating vehicles. According to a 2010 study by the US National Highway Traffic Safety Administration, vehicular communication systems could help avoiding up to 79% of all traffic accidents. [147]

The cooperative operation of AVs has many significant advantages. Researchers define three critical technologies [148]: (1) The cooperative driving connectivity between road users together with (2) *Big-Data* and (3) autonomous-vehicles' operation and control. Hult *et al.* [149] discussed the improvement in safety that results from cooperative driving (see Fig. 3).

According to the "Traffic Safety Facts Annual Report of 2017" [150], more than 80% of the accidents with known and reported factors were caused by human error. Poor lane keeping was responsible for 8% of those accidents, and drivers

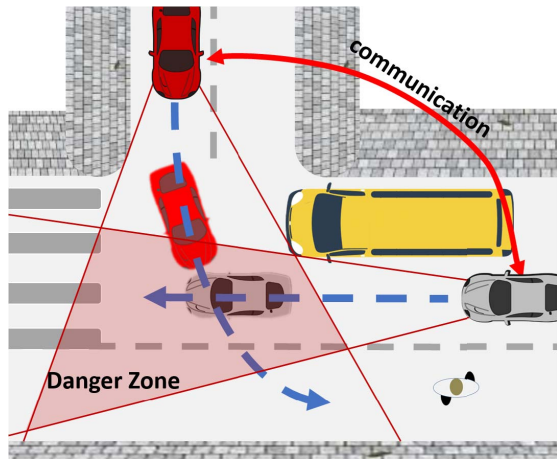


Fig. 3. Vehicle coordination relies on tight interaction between control, communication, and sensing [149].

under the influence of drugs, alcohol or medication were responsible for 12% of the accidents. Autonomous driving in general, and cooperative driving in particular, is widely considered to greatly increase road safety based on these factors.

Moreover, Zhou *et al.* [151] showed that cooperative control may significantly improve the smoothness of vehicular flow and increase road capacity in comparison to human-driven vehicles. They formulate a control law for vehicles' acceleration in response to the actions of surrounding vehicles. A discussion about ecological impact and fuel consumption can be found in [152]. Both fuel consumption and air pollution are reduced with the use of cooperative AVs (see also [153]).

The dependency level of an individual vehicle on a central unit, a controller, in its decision making was discussed in the literature. Reference [154] presented an algorithm for cooperative control of AVs using a multi-agent system. The authors formulated multi-layer reservation policies to manage the interactions between vehicles, with the aim of reducing energy consumption, increasing the smoothness of traffic flow, and increasing intersection throughput. In [155] researchers presented an algorithm for controlling the speed of an AV to follow a speed-profile generated for cooperative AVs. The algorithm monitors control messages that include the current desired speed, as well as the future speed-profile to overcome anomalous communications. In [156] the authors presented a three layer algorithm for cooperative lane-changing. Although the vehicles share information, the decision making is done independently.

#### A. Cooperative Sensing

Cooperative sensing enables information sharing by all road users and stationary devices located in the same environment, which provides road users with observations beyond the line-of-sight and the field-of-view. However, it introduces new problems such as how to locate all observations on the same map, identification of vehicles, high volume of communication, privacy invasion, etc. The authors in [157] presented a framework to deal with those challenges and demonstrated it on a group of AVs, each equipped with a single LIDAR

and a single camera. The communication and control were conducted by the open-source libraries of ROS (Robotic Operating System). In [158] the authors presented a cooperative sensing scheme that improves the vehicle's capabilities, which they named *see-through*, *lifted-seat* and *satellite-view*. The authors investigated the improvements of such cooperative sensing to the driving safety and the smoothness of the vehicle manoeuvres. Based on the literature review, it seems that this important subject should be further investigated.

#### B. Infrastructure to Vehicle Communication

Infrastructure to Vehicle (I2V) communication was considered a critical technology for road safety even before AVs became popular. For example, [159] exemplified the safety improvement and the positive attitude of human drivers to I2V systems.

AVs can send and receive data from stationary infrastructure devices in the vicinity. I2V communication includes monitoring vehicles [160], as well as other road users such as cyclists and pedestrians. Pedestrian monitoring is essential for AD in urban areas. Today, many streets have 24/7 surveillance cameras for traffic monitoring and security, and the big data from these cameras' networks provides beneficial data for AVs. Today, however, the control of most AVs is based on the vehicle's onboard sensors alone, yet, fusion with additional external data will increase performance for pedestrian tracking and accident avoidance. The use of street-view cameras was demonstrated by Kristoffersen *et al.* [161], where thermal cameras were used in complex scenarios with changing light conditions and existence of many pedestrians occluding one another. They introduced a stereo thermal camera setup for pedestrian counting, and investigated the reconstruction of 3D points in a pedestrian-crowded street with two thermal cameras. They then proposed an algorithm for pedestrian counting based on clustering and tracking the 3D point clouds.

Reference [162] presented an improved GPS localization system supported by I2V. Localization of vehicles based on GPS is impossible in many scenarios, especially cluttered urban areas. In such scenarios, I2V communications can provide accurate localization of vehicles. Reference [163]. I2V can also improve the AV decision making. Perumal *et al.* [164] presented an algorithm for AV motion planning based on observations for localization and for locating moving obstacles (road users). Grembek *et al.* [165] presented an algorithm for intelligent intersections based on I2V observations that compensates for insufficient information, leading to improved safety.

Another issue for consideration is the requirement for seamless connectivity of vehicles and infrastructure devices. Researchers (e.g., [166], [167]) are developing methods that apply multi-path TCP (Transmission Control Protocol) communication in multi-radio access technologies or by multi-hop clustering approach (e.g., a node can use other nodes as relays) using a Wi-Fi gateway roadside units installed every 3 km. In [168], the authors presented a roadside unit equipped with multiple antennas for network capacity improvement,



and provided an evaluation of the packet error probability by antenna correlation.

### C. Communication Between AVs and Pedestrians (V2P)

For safe AD in urban environment, communication of AVs with other road users, in particular pedestrians, is required [169]. Habibovic *et al.* [170] stated that communication between AVs and other road users that enables negotiation is essential, and examined some external devices and negotiation methods. They concluded that more research must be conducted in order to formulate an agreed standard, or language for this type of communication. Dey and Terken [171] studied the significance of eye contact and gestures between pedestrians and drivers. They found that motion patterns of the vehicle are more effective than eye contact for efficient traffic negotiations. These findings open an opportunity for efficient communication between pedestrians and AVs. Researchers also presented optional devices to support such communication, for example in [172] a visual interface is presented. Bazilial *et al.* [173] provided a survey of external human-machine interfaces (eHMIs). They found that textual eHMIs are clearer for a pedestrian than other methods. Moreover, they investigated how the text color and perspective of the textual message affect the comprehension of the message, and found that egocentric eHMIs are clearer.

In addition to the sensor system on the AV, communicating awareness and intent in AV-pedestrian interaction was considered in [174]. In this paper, the researchers presented the usefulness of interfaces that explicitly communicate awareness and intent of AVs to pedestrians, focusing on crosswalk scenarios. They found that interfaces communicating vehicle awareness and intent can help pedestrians attempting to cross. According to the research, the communication method should use a combination of visual, auditory, and physical means (e.g., a phone held by a participant that vibrates when it is safe to cross).

### D. Vehicle to Vehicle Communication

Vehicle to vehicle (V2V) communication is more difficult to implement due to its decentralized structure. V2V is based on information sharing between a group of vehicles in the same vicinity. This obviously requires communication technology and protocol agreements (see CAR2CAR Consortium [175]). By using V2V capabilities, the vehicles may also serve as routers and allow communication over multi-hop to distant vehicles and roadside stations. Challenges requiring consideration include communication delays, partial measurements, privacy and safety aspects. For example, in [176], the authors presented an approach for an AV collision warning system that is robust to communication uncertainty. Note that although the communication between AVs may significantly improve the traffic performance, it also holds risks, particularly in terms of cyber security. Amoozadeh *et al.* [177] showed by simulations that an insider attack can cause significant damage to an AV's control, and suggest some principals to improve AV cyber security.

## V. CURRENT GAPS

Autonomous vehicles are the near-future of transportation. The intense research of the industry's big players such as Google and Tesla will make transportation safer, more comfortable, more efficient, and more common. While in 2019, about 31 million vehicles were driving with some level of automation worldwide, according to Statista Research Department this number is expected to grow to 54 million in the next five years [178]. Nevertheless, most of the research today is focused on designing an AV that will be able to drive in today's roads alongside human-driven vehicles. According to the cited research papers (and the authors' view), some important points are still in the development stage and need more research.

The following list presents gaps that are unique to the AD field and not considered by other disciplines. We believe that the AV field should focus on the following list in the further development in order to expedite the adoption of autonomous vehicles technology.

### A. Environmental Sensors

- One of the ways to control AVs is to consider the vehicles as a cooperative system rather than individual entities. In such a case, the V2I together with V2C plays a major role in the AVs control process as external sensors are connected to control system. Implementation of efficient collective-information-sharing requires an array of sensors utilizing environmental sensors such as street/road cameras, as well as onboard sensors together with efficient sensors fusion procedures and reliable communication networks. Today, all leading AV manufacturers are developing control systems that rely entirely on the vehicle's on-board sensor system. As the AV market grows, the needs and opportunities for data sharing will increase. Governments and local authorities should direct resources from traditional road infrastructure to advanced infrastructures that support this data sharing. Such an upgrade does not necessarily involve initial high financial investments since many roads are already being monitored for traffic control, safety and security. At this stage we find that the gaps are mainly in the development of data fusion and information analysis algorithms. These algorithms include hazards' identification, road users' trajectory prediction, and schemes for alerting upcoming vehicles' failures. In addition, a high volume of data may enable the implementation of algorithms for the prediction of other road user behavior (pedestrians, cyclists, etc.).

### B. Robust and Distributed Communication Network

- Since the required capacity of information transfer for AD is very high and the number of users is expected to increase, there is a need for a robust and distributed communication network. The vision of cooperative sensing requires a reliable communication network. Data collection from street/road cameras in order to monitor all road users require further research. This should be integrated using conventional protocols for data sharing. Pedestrians should be connected to the communication network as well. V2V and V2I communication differs

from V2P since pedestrians' ability to receive information is restricted to small mobile devices (e.g., smart phones) and to limited human perception capacities. In addition, V2I lacks the ability to fully integrate the pedestrians in the control schemes. Even though researchers have been investigating this challenge for several years, this field requires further development.

### C. Cooperative Interaction

- Cooperative sensing and communication are basic requirements for cooperative interaction between vehicles and other road users. A centralized control may be implemented with different levels of centralization. Obviously, cooperative operation of AVs can be realized only when most of the vehicles are controlled by a centralized controller. These two prerequisites are not fully available yet. Cooperative operation is expected to improve the efficiency of driving with regard to traffic flow, power consumption, safety and comfort. Decision making in potentially fatal scenarios is a complex issue. When the AV control scheme is designed by the vehicle manufacturers that are committed to the safety of their customers, the control system will probably choose the safety of the AV passengers over the safety of other road users in potentially fatal scenarios. This field of research should be deeply investigated, given that the required infrastructures for the implementation of centralized AV control, such as 5G communication and high coverage by street cameras, will be available in the near future.

### D. Ethical and Legal Issues

- The AV technology introduces many ethical and legal questions. Preemption, give way for emergency vehicles, considerations for decision making in cases where an accident is inevitable, giving pedestrians traffic priority, the responsibility of the AV user versus the vehicle manufacturer are just a few examples for these type of questions. Jurists and researchers must formulate ethical considerations for AV decision making and data sharing, in keeping with the technology advancement. Furthermore, governments should implement legislation of new traffic laws and appropriate behavior for AVs, as well as standardization of road infrastructure suitable for AVs, such as communication networks, environmental sensors, road signs, etc.

### E. AVs Standardisation -

Although AVs are already operating in several cities around the world, still some gaps are needed to be handled in terms of standardization. The first one is to standardise functional requirements, functional architecture and interfaces between the different components involved in the AD tasks. For example, the automotive industry have started to consider the introduction of artificial intelligence algorithms in the ADAS and AD systems. These standardization activities are related to functional safety (ISO 26262) and Safety of the Intended Functionality (ISO 21448). The safety problem related to deployment of AI software in automotive system products is still open [179]. In addition, the researchers in [180] discuss the aspect of cyber security of autonomous vehicles. Cyber attacks on various sensors and on-board cameras have revealed several

vulnerabilities of the autonomous vehicles. The presence of wireless communication-based technologies for cooperative driving is inevitable, so reliable and secure data sharing must be applied.

Apart from the gaps mentioned above, we identify a few more technological gaps that are not directly related to the development of AD; however, they might significantly influence the evolution of AV technology.

- 1) *The High Price Tag of the Sensor Suit* - some researchers point out that this issue will delay the uptake of Avs [181], [182]. More algorithms using alternative sensor input data to LiDAR will lower the costs of the technology, for example, 3D observation using a mono camera.
- 2) *Sensor Data Fusion*: - these methods will improve the robustness to weather and other environmental conditions.
- 3) *Artificial Intelligence*: - utilizing AI as a tool for data analysis and decision making for AVs requires further research.

## VI. THE TRENDS OF RESEARCH FIELDS RELATED TO AUTONOMOUS DRIVING

Google Trends is a data source for various research fields that may be used for prediction [183], [184]. For example, real-time economic activity [185], Real-Time Surveillance of Disease Outbreaks [186] or for investigating the general interest in the robotics field [187]. Google trends data is also used in the AV field for scientometric analysis [188]. We now provide a short discussion on the popularity of technologies and research areas related to AD, as expressed by the number of search results listed in Google Scholar (GS) and the Web of science (WOS) over the past several years. For better accessibility to the leading research works, Table II depicts samples of AV main topics research through the last two decades.

These result can assists researchers in focusing their work on popular areas, as well as direct them towards other areas that are still in the early stages of development. Although there are several academic search engines like 'Scopus' and 'Web of science,' we give precedence to GS and to WOS. We chose GS because, in contrast to other engines and tools, it searches cover the entire web and is not limited to core collections. The WOS was chosen as it is considered to be the most reliable and objective data base of academic publications.

The trends analysis methodology used in this section was as follows: We searched in Google Scholar keywords e.g. "autonomous vehicle", "camera" and "autonomous driving", while limiting the results to a specific year. In the Web Of Science core collection the search was limited to the topic (i.e. title, abstract and keywords). The results are presented in the following graphs. As expected, the number of search results in the WOS is much lower than that in GS since WOS covers only the core collection academic journals and conferences while GS covers all publications, including non-academic publication, patents, private webpages etc. We present the number of search results per year over the last two decades.



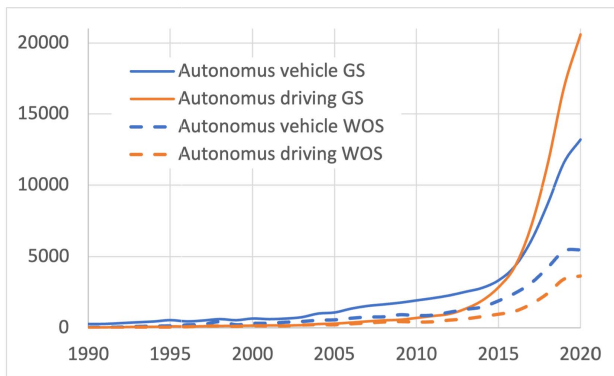


Fig. 4. Number of search results in Google Scholar (GS) and Web of Science (WOS) per year.

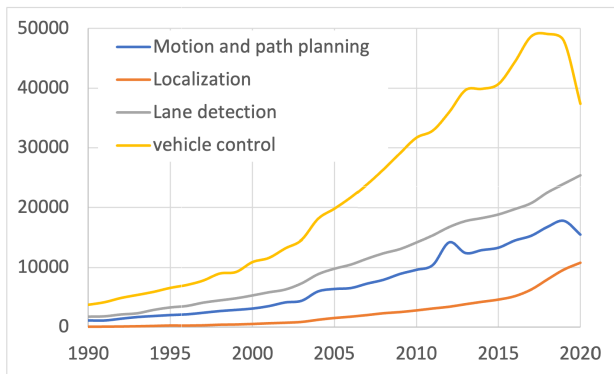


Fig. 5. Number of search results in Google Scholar per year.

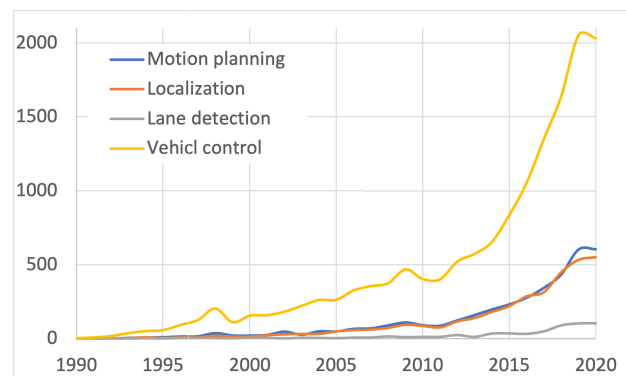


Fig. 6. Number of search results in web of science per year.

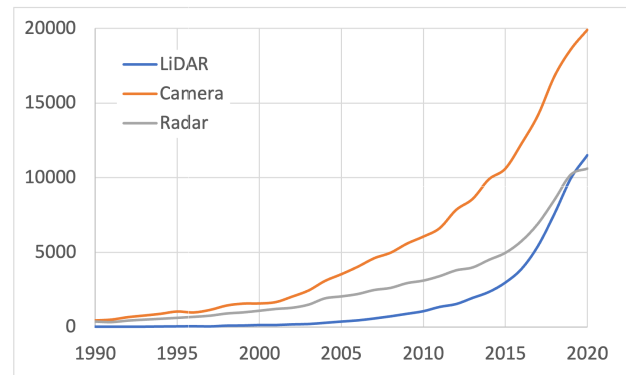


Fig. 7. Number of search results in Google Scholar per year.

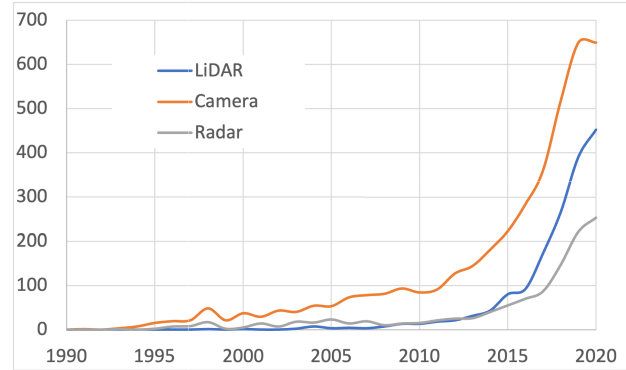


Fig. 8. Number of search results in web of science per year.

The graphs below (Figures 4-11) present various terms according to their affiliation. In both search engines, we counted only search results that included the terms “autonomous-vehicle” or “autonomous-driving” together with the term that was checked. This prevents counting terms related to other disciplines, e.g., the term camera gets billions of search results that are not necessarily related to AD or to AV.

Fig. 4 depicts the number of Google Scholar and Web Of Science search results for the terms “autonomous vehicle” and “autonomous driving” per year between 1990 and 2020. The graphs indicate that until 2010 the growth rate of both AD and AV research was moderate and similar, with AV research leading in the number of search results per year. Then, from 2010 onwards, there was an exponential increase in both terms. Note that the term “autonomous vehicle” may include other research areas like unmanned aerial/underwater vehicles etc., while AD is unique to this survey’s areas, thus, the actual trend is even sharper, in addition to the larger absolute number of results for AD compared with AV. Furthermore, when discussing the trends of specific research areas within AD and AV, the relative number of entries of a specific area must be considered in relations to the entire entries.

The number of search results of the terms related to the basic operations of AD are presented in Fig. 5 for GS and in Fig. 6 for WOS. Again, the number of search results in WOS is significantly lower than in GS. Note that the search results that included both AV or AD together with the search term were counted. The increase of these terms’ appearance is conservative compared with the terms AV and

AD displayed in Fig. 4. One explanation is that these subjects are common in other disciplines such as general robotics and systems control, making them commonly used by many other researchers. According to the graphs, we believe that the rising rate of these terms in relation to general control and robotics will decrease in the next years, while we expect the rate to increase in relation to AD and AV. According to the graph, the number of search results related to vehicle control has declined since 2018, while publications related to lane detection and localization increased.

The popularity of different sensors used in the operation of AVs is presented in Figures 7 and 8. Both graphs indicate the same phenomena, while the number of researches that rely on cameras increases continuously and steadily due to the development of learning algorithms, LiDARs became

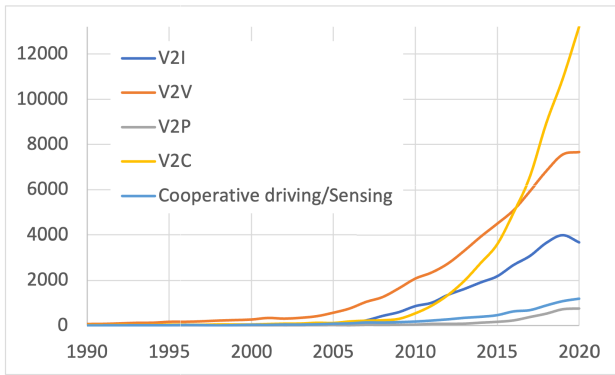


Fig. 9. Number of search results in google scholar per year.

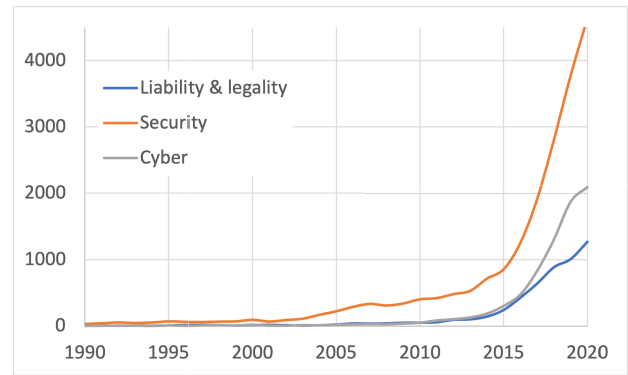


Fig. 11. Number of search results in google scholar per year.

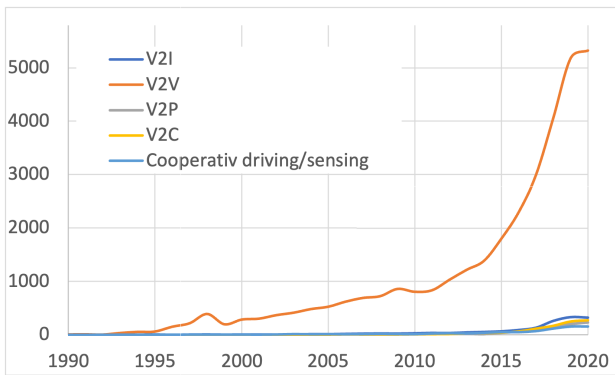


Fig. 10. Number of search results in web of science per year.

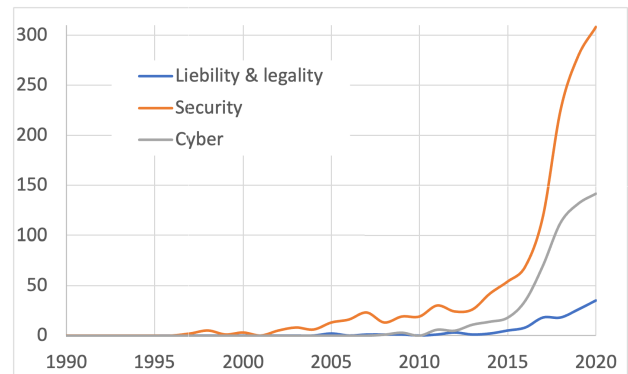


Fig. 12. Number of search results in web of science per year.

commonly used only in the middle of the previous decade. Due to its cost, LiDAR systems were involved in only a few research papers until about 2015, when their price dropped. Radar technology, on the other hand, was attractive at the beginning of the analyzed period, but in recent years (since 2019) LiDAR technology is more common in research. Radar was a complementary sensor to cameras since it is robust for visibility conditions, but it lost its attraction when LiDARs became popular.

This survey’s results emphasize the advantages of the collaborative operation for AVs and AD. Figure 9 presents the number of search results of the variants of V2X and cooperative driving terms. The results indicate that searching for these terms became common about 2007-2010. Furthermore, the appearance of the term Vehicle to Cloud (V2C) was less common at the outset, but has increased in the last decade, and currently leads the research in the field (as expressed by the number of search results in Google Scholar). Contrary to our initial assumption, collaborative operation of AVs is not attractive in the current literature. We believe that this is a result of the lack of attention that this area receives from the AV manufacturers. Finally, V2P has the lowest number of search results, even though this technology is essential for pedestrian safety. One explanation for this is that it requires multidisciplinary research technology combined with human behavior skills.

Liability and legal considerations of AD are only at the early stage of development. Figure 11 presents search results of the terms “security” and “cyber”, which complement AD.

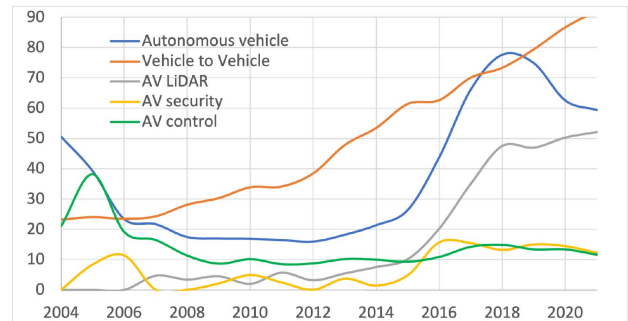


Fig. 13. Google trends per year.

We believe that as AVs become more common in public roads, research on the liability and legal considerations will increase dramatically.

Fig. 13 depicts the Google-Trends (GT) search queries popularity in the years 2004-2021 (2004 was the earliest available data). Since GT provides data in a monthly resolution, the data in Figure 13 is presented as the mean through a year. GT does not provide absolute values of the number of queries, only relative ones. The month with maximal queries gets a 100% value, and all others are measured relative to it. Each term is presented relatively to its own average value, so the values are not a comparison between the absolute popularity of the terms. The trends reflected in the graph indicate only the measure of interest in these terms. Note that many of the terms in the graphs of GS and WOS do not have enough data to be displayed as there are not enough previous searches on

the specific terms. However, the terms that we use here present examples of all groups of areas as discussed in this paper.

## VII. SUMMARY

In this review paper we present the technological development of autonomous vehicles and autonomous driving. We first differentiate between the terms “Autonomous Vehicles (AV)” and “Autonomous Driving (AD)”, where AD is a wider term that incorporates AV as well as other terms and technologies. The paper then presents the relevant research directly related to AVs (e.g., vehicle control, lane detection, localization, and motion planning), and other terms such as cooperative driving, communication and road user behavior. We then discuss the technological gaps in AVs as well as in AD. While the current state of technology provides sufficient autonomy for a group of vehicles operating in dedicated and controlled environments, further research and development is required for the integration of AD in existing traffic and roads. In particular, the integration of AVs with other road users (e.g. vehicles controlled by humans, bicycle users and pedestrians) requires further research, particularly in areas such as cooperative driving, V2X infrastructure, human behavior and legislation. Finally, the paper presents an analysis of the trends in AV and AD as expressed by the number of annual search results listed in Google Scholar and the Web Of Science over the last two decades. The analysis clearly indicates a rapid growth in interest in AD and AV (with a significant increase in AD compared with AV since 2017). It also indicates moderate increase in “traditional” research areas such as motion planning, localization and vehicle control, with more significant increase in the use of onboard sensors, particularly camera and LiDAR technologies. An exponential increase in the number of search results in the term V2C (Vehicle to Cloud) indicates that further research is required in areas such as V2I and V2P. These research areas require multidisciplinary and interdisciplinary approaches that include specialist in the field of behavioral science, as well as experts in liability and legislation.

## REFERENCES

- [1] M. Sentinel, “Phantom auto’ will tour city,” *Milwaukee Sentinel*, vol. 4, Dec. 1926.
- [2] T. Kanade, C. Thorpe, and W. Whittaker, “Autonomous land vehicle project at CMU,” in *Proc. ACM 14th Annu. Conf. Comput. Sci.*, 1986, pp. 71–80.
- [3] D. Neil, “Who’s behind the wheel? nobody. the driverless car is coming. and we all should be glad it is,” *Wall Street J.*, Sep. 2012. [Online]. Available: <https://www.proquest.com/newspapers/whos-behind-wheel-nobody-driverless-car-is-coming/docview/1064085009/se-2?accountid=40023>
- [4] BBC. (2013). *Toyota Sneak Previews Self-Drive Car Ahead of Tech Show*. [Online]. Available: <https://www.bbc.com/news/technology-20910769>.
- [5] International Standard of Automotive Engineers (2016). *Automated Driving Levels of Driving Automation are Defined in New SAE International Standard J3016*. [Online]. Available: [https://cdn.oemoffhighway.com/files/base/acbm/oooh/document/2016/03/automated\\_driving.pdf](https://cdn.oemoffhighway.com/files/base/acbm/oooh/document/2016/03/automated_driving.pdf).
- [6] W. Shi, M. B. Alawieh, X. Li, and H. Yu, “Algorithm and hardware implementation for visual perception system in autonomous vehicle: A survey,” *Integration*, vol. 59, pp. 148–156, Sep. 2017.
- [7] J. Van Brummelen, M. O’Brien, D. Gruyer, and H. Najjaran, “Autonomous vehicle perception: The technology of today and tomorrow,” *Transp. Res. C, Emerg. Technol.*, vol. 89, pp. 384–406, Apr. 2018.
- [8] S. B. Sarkar and B. C. Mohan, “Review on autonomous vehicle challenges,” in *First International Conference on Artificial Intelligence and Cognitive Computing*. Singapore: Springer, 2019, pp. 593–603.
- [9] X. Di and R. Shi, “A survey on autonomous vehicle control in the era of mixed-autonomy: From physics-based to AI-guided driving policy learning,” *Transp. Res. C, Emerg. Technol.*, vol. 125, Apr. 2021, Art. no. 103008.
- [10] I. Emmanuel, “Fuzzy logic-based control for autonomous vehicle: A survey,” *Int. J. Educ. Manage. Eng.*, vol. 7, no. 2, p. 41, 2017.
- [11] O. Sharma, N. C. Sahoo, and N. B. Puhana, “A survey on smooth path generation techniques for nonholonomic autonomous vehicle systems,” in *Proc. 45th Annu. Conf. IEEE Ind. Electron. Soc. (IECON)*, Oct. 2019, pp. 5167–5172.
- [12] S. Kuutti, S. Fallah, K. Katsaros, M. Dianati, F. Mccullough, and A. Mouzakitis, “A survey of the state-of-the-art localization techniques and their potentials for autonomous vehicle applications,” *IEEE Internet Things J.*, vol. 5, no. 2, pp. 829–846, Apr. 2018.
- [13] M. S. Güzel, “Autonomous vehicle navigation using vision and mapless strategies: A survey,” *Adv. Mech. Eng.*, vol. 5, Jan. 2013, Art. no. 234747.
- [14] T. T. O. Takleh, N. A. Bakar, S. A. Rahman, R. Hamzah, and Z. A. Aziz, “A brief survey on SLAM methods in autonomous vehicle,” *Int. J. Eng. Technol.*, vol. 7, no. 4, pp. 38–43, 2018.
- [15] M. Imad, M. A. Hassan, H. Junaid, and I. Ahmad, “Navigation system for autonomous vehicle: A survey,” *J. Comput. Sci. Technol. Stud.*, vol. 2, no. 2, pp. 20–35, 2020.
- [16] U. Z. A. Hamid, H. Zamzuri, and D. K. Limbu, “Internet of vehicle (IoV) applications in expediting the implementation of smart highway of autonomous vehicle: A survey,” in *Performability in Internet of Things*. Cham, Switzerland: Springer, 2019, pp. 137–157.
- [17] A. Boubakri and S. M. Gammar, “Intra-platoon communication in autonomous vehicle: A survey,” in *Proc. 9th IFIP Int. Conf. Perform. Eval. Modeling Wireless Netw. (PEMWN)*, Dec. 2020, pp. 1–6.
- [18] J. Zhang, E. Vinkhuysen, and M. Cefkin, “Evaluation of an autonomous vehicle external communication system concept: A survey study,” in *Proc. Int. Conf. Appl. Hum. Factors Ergonom.* Cham, Switzerland: Springer, 2017, pp. 650–661.
- [19] O. A. Maghraoui *et al.*, “Shared autonomous vehicle services and user taste variations: Survey and model applications,” *Transp. Res. Proc.*, vol. 47, pp. 3–10, Jan. 2020.
- [20] S. Kuutti, R. Bowden, Y. C. Jin, P. Barber, and S. Fallah, “A survey of deep learning applications to autonomous vehicle control,” *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 2, pp. 712–733, Feb. 2020.
- [21] S. Devi, P. Malarvezhi, R. Dayana, and K. Vadivukkarasi, “A comprehensive survey on autonomous driving cars: A perspective view,” *Wireless Pers. Commun.*, vol. 114, no. 3, pp. 2121–2133, May 2020.
- [22] R. McAllister *et al.*, “Concrete problems for autonomous vehicle safety: Advantages of Bayesian deep learning,” in *Proc. Int. Joint Conf. Artif. Intell.*, Aug. 2017, pp. 4745–4753.
- [23] J. Betz *et al.*, “Autonomous vehicles on the edge: A survey on autonomous vehicle racing,” 2022, *arXiv:2202.07008*.
- [24] A. D. Kumar, K. N. R. Chebrolu, R. Vinayakumar, and K. P. Soman, “A brief survey on autonomous vehicle possible attacks, exploits and vulnerabilities,” 2018, *arXiv:1810.04144*.
- [25] D. J. Fagnant and K. Kockelman, “Preparing a nation for autonomous vehicles: Opportunities, barriers and policy recommendations,” *Transp. Res. A, Policy Pract.*, vol. 77, pp. 167–181, Jul. 2015.
- [26] SAE On-Road Automated Vehicle Standards Committee, “Taxonomy and definitions for terms related to on-road motor vehicle automated driving systems,” *SAE Standard J.*, vol. 3016, pp. 1–16, Jan. 2014.
- [27] *Taxonomy and Definitions for Terms Related to Driving Automation Systems for on-Road Motor Vehicles (J3016)*, Society for Automotive Engineering, Warrendale, PA, USA, 2016.
- [28] T. Sattler *et al.*, “Benchmarking 6DOF outdoor visual localization in changing conditions,” in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*, Jun. 2018, pp. 8601–8610.
- [29] K. Wong, E. Javanmardi, M. Javanmardi, and S. Kamijo, “Estimating autonomous vehicle localization error using 2D geographic information,” *ISPRS Int. J. Geo-Inf.*, vol. 8, no. 6, p. 288, Jun. 2019.
- [30] M. J. Choi, J. K. Suhr, K. Choi, and H. G. Jung, “Low-cost precise vehicle localization using lane endpoints and road signs for highway situations,” *IEEE Access*, vol. 7, pp. 149846–149856, 2019.
- [31] B. Browning, P. Hansen, E. Eade, D. Prasser, D. LaRose, and R. Zlot, “Autonomous vehicle localization using passive image data,” U.S. Patent 10474162, Nov. 12, 2019.
- [32] B. Browning, P. Hansen, E. Eade, D. Prasser, D. LaRose, and R. Zlot, “Autonomous vehicle localization using image analysis and manipulation,” U.S. Patent 10678262, Jun. 9, 2020.

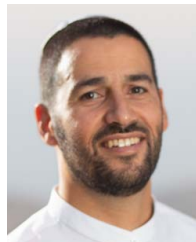
- [33] L. Wang, Y. Zhang, and J. Wang, "Map-based localization method for autonomous vehicles using 3D-LiDAR," *IFAC-PapersOnLine*, vol. 50, no. 1, pp. 276–281, 2017.
- [34] S. Z. A. Mukhtar, V. B. Saputra, S. Verma, K. Zhang, and A. H. Adiwahono, "Sparse-3D LiDAR outdoor map-based autonomous vehicle localization," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, Nov. 2019, pp. 1614–1619.
- [35] P. DeBitetto, M. Graham, T. Jones, P. Lommel, and J. Demerly, "Autonomous vehicle: Vehicle localization," U.S. Patent 15280296, Mar. 29, 2018.
- [36] S.-L. Yu, T. Westfechtel, R. Hamada, K. Ohno, and S. Tadokoro, "Vehicle detection and localization on bird's eye view elevation images using convolutional neural network," in *Proc. IEEE Int. Symp. Saf., Secur. Rescue Robot. (SSRR)*, Oct. 2017, pp. 102–109.
- [37] G. Johansson and M. Wastebly, "Hybrid map for autonomous commercial vehicles-global localization using topological mapping and machine learning," M.S. thesis, Dept. Appl. Mech., Chalmers Univ. Technol., Gothenburg, Sweden, 2017.
- [38] J. McCall and M. M. Trivedi, "Video-based lane estimation and tracking for driver assistance: Survey, system, and evaluation," *IEEE Trans. Intell. Transp. Syst.*, vol. 7, no. 1, pp. 20–37, Mar. 2006.
- [39] S. Zhou, Y. Jiang, J. Xi, J. Gong, G. Xiong, and H. Chen, "A novel lane detection based on geometrical model and Gabor filter," in *Proc. IEEE Intell. Vehicles Symp.*, Jun. 2010, pp. 59–64.
- [40] M. Aly, "Real time detection of lane markers in urban streets," in *Proc. IEEE Intell. Vehicles Symp.*, Jun. 2008, pp. 7–12.
- [41] C. Lee and J.-H. Moon, "Robust lane detection and tracking for real-time applications," *IEEE Trans. Intell. Transp. Syst.*, vol. 19, no. 12, pp. 4043–4048, Dec. 2018.
- [42] L. N. P. Boggavarapu, R. S. Vaddi, K. R. Anne, H. D. Vankayalapati, and J. K. Munagala, "A robust multi color lane marking detection approach for Indian scenario," *Int. J. Adv. Comput. Sci. Appl.*, vol. 2, no. 5, p. 71, 2011.
- [43] Z. Teng, J.-H. Kim, and D.-J. Kang, "Real-time lane detection by using multiple cues," in *Proc. ICCAS*, Oct. 2010, pp. 2334–2337.
- [44] T.-Y. Sun, S.-J. Tsai, and V. Chan, "HSI color model based lane-marking detection," in *Proc. IEEE Intell. Transp. Syst. Conf.*, Sep. 2006, pp. 1168–1172.
- [45] P. M. Daigavane and P. R. Bajaj, "Road lane detection with improved Canny edges using ant colony optimization," in *Proc. 3rd Int. Conf. Emerg. Trends Eng. Technol.*, Nov. 2010, pp. 76–80.
- [46] Y. Otsuka, S. Muramatsu, H. Takenaga, Y. Kobayashi, and T. Monji, "Multitype lane markers recognition using local edge direction," in *Proc. Intell. Vehicle Symp.*, vol. 2, 2002, pp. 604–609.
- [47] H. Twaddle, T. Schendzielorz, and O. Fakler, "Bicycles in urban areas: Review of existing methods for modeling behavior," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 2434, no. 1, pp. 140–146, Jan. 2014.
- [48] D. Yao, Y. Zhang, L. Li, Y. Su, S. Cheng, and W. Xu, "Behavior modeling and simulation for conflicts in vehicles-bicycles mixed flow," *IEEE Intell. Transp. Syst. Mag.*, vol. 1, no. 2, pp. 25–30, Summer 2009.
- [49] Y. Li, Y. Ni, J. Sun, and Z. Ma, "Modeling the illegal lane-changing behavior of bicycles on road segments: Considering lane-changing categories and bicycle heterogeneity," *Phys. A, Stat. Mech. Appl.*, vol. 541, Mar. 2020, Art. no. 123302.
- [50] T. S. Combs, L. S. Sandt, M. P. Clamann, and N. C. McDonald, "Automated vehicles and pedestrian safety: Exploring the promise and limits of pedestrian detection," *Amer. J. Preventive Med.*, vol. 56, no. 1, pp. 1–7, Jan. 2019.
- [51] M. Ullah, H. Ullah, N. Conci, and F. G. B. De Natale, "Crowd behavior identification," in *Proc. IEEE Int. Conf. Image Process. (ICIP)*, Sep. 2016, pp. 1195–1199.
- [52] V. J. Kok, M. K. Lim, and C. S. Chan, "Crowd behavior analysis: A review where physics meets biology," *Neurocomputing*, vol. 177, pp. 342–362, Feb. 2016.
- [53] D. Helbing and A. Johansson, "Pedestrian, crowd, and evacuation dynamics," 2013, *arXiv:1309.1609*.
- [54] H. Zhou, S. B. Romero, and X. Qin, "An extension of the theory of planned behavior to predict pedestrians' violating crossing behavior using structural equation modeling," *Accident Anal. Prevention*, vol. 95, pp. 417–424, Oct. 2016.
- [55] S. Ye, L. Wang, K. H. Cheong, and N. Xie, "Pedestrian group-crossing behavior modeling and simulation based on multidimensional dirty faces game," *Complexity*, vol. 2017, pp. 1–12, Jan. 2017.
- [56] D. S. Pawar, V. Kumar, N. Singh, and G. R. Patil, "Analysis of dilemma zone for pedestrians at high-speed uncontrolled midblock crossing," *Transp. Res. C, Emerg. Technol.*, vol. 70, pp. 42–52, Sep. 2016.
- [57] S. P. Hoogendoorn and P. H. Bovy, "Normative pedestrian behaviour theory and modelling," in *Transportation and Traffic Theory in the 21st Century*. Norwell, MA, USA: Wolters Kluwer, 2002, pp. 219–245.
- [58] V. J. Blue and J. L. Adler, "Cellular automata microsimulation for modeling bi-directional pedestrian walkways," *Transp. Res. B, Methodol.*, vol. 35, no. 3, pp. 293–312, Mar. 2001.
- [59] D. C. Duives, W. Daamen, and S. P. Hoogendoorn, "State-of-the-art crowd motion simulation models," *Transp. Res. C, Emerg. Technol.*, vol. 37, pp. 193–209, Dec. 2013.
- [60] E. Papadimitriou, G. Yannis, and J. Golias, "A critical assessment of pedestrian behaviour models," *Transp. Res. F, Traffic Psychol. Behav.*, vol. 12, no. 3, pp. 242–255, 2009.
- [61] N. Bellomo, B. Piccoli, and A. Tosin, "Modeling crowd dynamics from a complex system viewpoint," *Math. Models Methods Appl. Sci.*, vol. 22, Aug. 2012, Art. no. 1230004.
- [62] H. Guo, Z. Gao, X. Yang, and X. Jiang, "Modeling pedestrian violation behavior at signalized crosswalks in China: A hazards-based duration approach," *Traffic Injury Prevention*, vol. 12, no. 1, pp. 96–103, Jan. 2011.
- [63] S. Hacothen, N. Shvalb, and S. Shoval, "Dynamic model for pedestrian crossing in congested traffic based on probabilistic navigation function," *Transp. Res. C, Emerg. Technol.*, vol. 86, pp. 78–96, Jan. 2018.
- [64] Y. Hashimoto, Y. Gu, L. T. Hsu, M. Iryo-Asano, and S. Kamijo, "A probabilistic model of pedestrian crossing behavior at signalized intersections for connected vehicles," *Transp. Res. C, Emerg. Technol.*, vol. 71, pp. 164–181, Oct. 2016.
- [65] W. Wang, H. Guo, Z. Gao, and H. Bubb, "Individual differences of pedestrian behaviour in midblock crosswalk and intersection," *Int. J. Crashworthiness*, vol. 16, no. 1, pp. 1–9, Apr. 2011.
- [66] J. Y. S. Lee and W. H. K. Lam, "Simulating pedestrian movements at signalized crosswalks in Hong Kong," *Transp. Res. A, Policy Pract.*, vol. 42, no. 10, pp. 1314–1325, 2008.
- [67] S. Bonnin, T. H. Weisswange, F. Kummert, and J. Schmuuederich, "Pedestrian crossing prediction using multiple context-based models," in *Proc. 17th Int. IEEE Conf. Intell. Transp. Syst. (ITSC)*, Oct. 2014, pp. 378–385.
- [68] W. Zeng, P. Chen, H. Nakamura, and M. Iryo-Asano, "Application of social force model to pedestrian behavior analysis at signalized crosswalk," *Transp. Res. C, Emerg. Technol.*, vol. 40, pp. 143–159, Mar. 2014.
- [69] S. Hacothen, S. Shoval, and N. Shvalb, "The paradox of pedestrian's risk aversion," *Accident Anal. Prevention*, vol. 142, Jul. 2020, Art. no. 105518.
- [70] Y. Xiao, Z. Gao, Y. Qu, and X. Li, "A pedestrian flow model considering the impact of local density: Voronoi diagram based heuristics approach," *Transp. Res. C, Emerg. Technol.*, vol. 68, pp. 566–580, Jul. 2016.
- [71] G. Waizman, S. Shoval, and I. Benenson, "Micro-simulation model for assessing the risk of vehicle-pedestrian road accidents," *J. Intell. Transp. Syst.*, vol. 19, no. 1, pp. 63–77, Jan. 2015.
- [72] J. Bohren *et al.*, "Little ben: The Ben Franklin racing team's entry in the 2007 DARPA urban challenge," *J. Field Robot.*, vol. 25, no. 9, pp. 598–614, 2008.
- [73] Y.-L. Chen *et al.*, "TerraMax™: Team Oshkosh urban robot," *J. Field Robot.*, vol. 25, no. 10, pp. 841–860, Oct. 2008.
- [74] B. Patz, Y. Papelis, R. Pillat, G. Stein, and D. Harper, "A practical approach to robotic design for the DARPA urban challenge," *J. Field Robot.*, vol. 25, no. 8, pp. 528–566, 2008.
- [75] S. J. Anderson, S. B. Karumanchi, and K. Iagnemma, "Constraint-based planning and control for safe, semi-autonomous operation of vehicles," in *Proc. IEEE Intell. Vehicles Symp.*, Jun. 2012, pp. 383–388.
- [76] C. Urmson *et al.*, "Autonomous driving in urban environments: Boss and the urban challenge," *J. Field Robot.*, vol. 25, no. 8, pp. 425–466, 2008.
- [77] D. Ferguson, T. M. Howard, and M. Likhachev, "Motion planning in urban environments," *J. Field Robot.*, vol. 25, nos. 11–12, pp. 939–960, Nov. 2008.
- [78] M. Likhachev and D. Ferguson, "Planning long dynamically feasible maneuvers for autonomous vehicles," *Int. J. Robot. Res.*, vol. 28, no. 8, pp. 933–945, 2009.
- [79] M. Montemerlo *et al.*, "Junior: The Stanford entry in the urban challenge," *J. Field Robot.*, vol. 25, no. 9, pp. 569–597, 2008.
- [80] Y. Kuwata, J. Teo, G. Fiore, S. Karaman, E. Frazzoli, and J. P. How, "Real-time motion planning with applications to autonomous urban driving," *IEEE Trans. Control Syst. Technol.*, vol. 17, no. 5, pp. 1105–1118, Sep. 2009.

- [81] D. Braid, A. Broggi, and G. Schmiedel, "The TerraMax autonomous vehicle," *J. Field Robot.*, vol. 23, no. 9, pp. 693–708, 2006.
- [82] J.-H. Ryu, D. Ogay, S. Bulavintsev, H. Kim, and J.-S. Park, "Development and experiences of an autonomous vehicle for high-speed navigation and obstacle avoidance," in *Frontiers of Intelligent Autonomous Systems*. Berlin, Germany: Springer, 2013, pp. 105–116.
- [83] S. Karaman, M. R. Walter, A. Perez, E. Frazzoli, and S. Teller, "Anytime motion planning using the RRT," in *Proc. IEEE Int. Conf. Robot. Autom.*, May 2011, pp. 1478–1483.
- [84] J. Borenstein and Y. Koren, "Real-time obstacle avoidance for fast mobile robots," *IEEE Trans. Syst., Man, Cybern.*, vol. 19, no. 5, pp. 1179–1187, Sep./Oct. 1989.
- [85] S. Hacothen, S. Shoval, and N. Shvalb, "Probability navigation function for stochastic static environments," *Int. J. Control, Autom. Syst.*, vol. 17, no. 8, pp. 2097–2113, Aug. 2019.
- [86] D. Baronov and J. Baillieul, "Autonomous vehicle control for ascending/descending along a potential field with two applications," in *Proc. Amer. Control Conf.*, Jun. 2008, pp. 678–683.
- [87] Y. Rasekhipour, A. Khajepour, S.-K. Chen, and B. Litkouhi, "A potential field-based model predictive path-planning controller for autonomous road vehicles," *IEEE Trans. Intell. Transp. Syst.*, vol. 18, no. 5, pp. 1255–1267, May 2017.
- [88] F. Yan, "Autonomous vehicle routing problem solution based on artificial potential field with parallel ant colony optimization (ACO) algorithm," *Pattern Recognit. Lett.*, vol. 116, pp. 195–199, Dec. 2018.
- [89] L. Makarem and D. Gillet, "Fluent coordination of autonomous vehicles at intersections," in *Proc. IEEE Int. Conf. Syst., Man, Cybern. (SMC)*, Oct. 2012, pp. 2557–2562.
- [90] M. Brown, J. Funke, S. Erlien, and J. C. Gerdes, "Safe driving envelopes for path tracking in autonomous vehicles," *Control Eng. Pract.*, vol. 61, pp. 307–316, Apr. 2017.
- [91] K. Moriawaki, "Autonomous steering control for electric vehicles using nonlinear state feedback  $H_\infty$  control," *Nonlinear Anal., Theory, Methods Appl.*, vol. 63, nos. 5–7, pp. e2257–e2268, Nov. 2005.
- [92] J. E. da Silva and J. B. de Sousa, "A dynamic programming approach for the motion control of autonomous vehicles," in *Proc. 49th IEEE Conf. Decis. Control (CDC)*, Dec. 2010, pp. 6660–6665.
- [93] T. Kessler *et al.*, "Roadgraph generation and free-space estimation in unknown structured environments for autonomous vehicle motion planning," in *Proc. 21st Int. Conf. Intell. Transp. Syst. (ITSC)*, Nov. 2018, pp. 2831–2838.
- [94] E. Xargay, V. Dobrokhodov, I. Kaminer, A. M. Pascoal, N. Hovakimyan, and C. Cao, "Time-critical cooperative control of multiple autonomous vehicles: Robust distributed strategies for path-following control and time-coordination over dynamic communications networks," *IEEE Control Syst. Mag.*, vol. 32, no. 5, pp. 49–73, Oct. 2012.
- [95] F. Zhang, J. Gonzales, S. E. Li, F. Borrelli, and K. Li, "Drift control for cornering maneuver of autonomous vehicles," *Mechatronics*, vol. 54, pp. 167–174, Oct. 2018.
- [96] M. Kissai, X. Mouton, B. Monsuez, D. Martinez, and A. Tapus, "Optimizing vehicle motion control for generating multiple sensations," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2018, pp. 928–935.
- [97] S. Magdici and M. Althoff, "Fail-safe motion planning of autonomous vehicles," in *Proc. IEEE 19th Int. Conf. Intell. Transp. Syst. (ITSC)*, Nov. 2016, pp. 452–458.
- [98] R. Solea and U. Nunes, "Trajectory planning and sliding-mode control based trajectory-tracking for cybercars," *Integr. Comput.-Aided Eng.*, vol. 14, no. 1, pp. 33–47, Jan. 2007.
- [99] R. Lattarulo, L. González, E. Martí, J. Matute, M. Marcano, and J. Pérez, "Urban motion planning framework based on N-Bézier curves considering comfort and safety," *J. Adv. Transp.*, vol. 2018, pp. 1–13, Jul. 2018.
- [100] M. Cunneen, M. Mullins, F. Murphy, D. Shannon, I. Furxhi, and C. Ryan, "Autonomous vehicles and avoiding the trolley (dilemma): Vehicle perception, classification, and the challenges of framing decision ethics," *Cybern. Syst.*, vol. 51, no. 1, pp. 59–80, Jan. 2020.
- [101] H. Wang, Y. Huang, A. Khajepour, D. Cao, and C. Lv, "Ethical decision-making platform in autonomous vehicles with lexicographic optimization based model predictive controller," *IEEE Trans. Veh. Technol.*, vol. 69, no. 8, pp. 8164–8175, Aug. 2020.
- [102] W. Schwarting, J. Alonso-Mora, and D. Rus, "Planning and decision-making for autonomous vehicles," *Annu. Rev. Control, Robot., Auton. Syst.*, vol. 1, no. 1, pp. 187–210, May 2018.
- [103] M. Allodi, A. Broggi, D. Giaquinto, M. Patander, and A. Prioletti, "Machine learning in tracking associations with stereo vision and LiDAR observations for an autonomous vehicle," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2016, pp. 648–653.
- [104] L. Li, K. Ota, and M. Dong, "Humanlike driving: Empirical decision-making system for autonomous vehicles," *IEEE Trans. Veh. Technol.*, vol. 67, no. 8, pp. 6814–6823, Aug. 2018.
- [105] D. Isele, R. Rahimi, A. Cosgun, K. Subramanian, and K. Fujimura, "Navigating occluded intersections with autonomous vehicles using deep reinforcement learning," in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, May 2018, pp. 2034–2039.
- [106] S. S. Banerjee, S. Jha, J. Cyriac, Z. T. Kalbarczyk, and R. K. Iyer, "Hands off the wheel in autonomous vehicles? A systems perspective on over a million miles of field data," in *Proc. 48th Annu. IEEE/IFIP Int. Conf. Dependable Syst. Netw. (DSN)*, Jun. 2018, pp. 586–597.
- [107] P. Koopman and M. Wagner, "Autonomous vehicle safety: An interdisciplinary challenge," *IEEE Intell. Transp. Syst. Mag.*, vol. 9, no. 1, pp. 90–96, Jan. 2017.
- [108] B. Mirchevska, C. Pek, M. Werling, M. Althoff, and J. Boedecker, "High-level decision making for safe and reasonable autonomous lane changing using reinforcement learning," in *Proc. 21st Int. Conf. Intell. Transp. Syst. (ITSC)*, Nov. 2018, pp. 2156–2162.
- [109] Y. Ohshima, "Control system for automatic automobile driving," in *Proc. IFAC Tokyo Symp. Syst. Eng. Control Syst. Design*, 1965, pp. 90–96.
- [110] R. E. Fenton and R. J. Mayhan, "Automated highway studies at the Ohio State University—An overview," *IEEE Trans. Veh. Technol.*, vol. 40, no. 1, pp. 100–113, Feb. 1991.
- [111] S. Shoval, J. P. Zybur, and D. W. Grimaudo, "Robot driver for guidance of automatic durability road (ADR) test vehicles," in *Proc. IEEE Int. Conf. Robot. Autom.*, vol. 2, May 1998, pp. 1767–1772.
- [112] S. Thrun *et al.*, "Stanley: The robot that won the DARPA grand challenge," *J. Field Robot.*, vol. 23, no. 9, pp. 661–692, Sep. 2006.
- [113] *Uniform Provisions Concerning the Approval of Motor Vehicles With Regard to the Advanced Emergency Braking System (AEBS) for M1 and N1 Vehicles*, United Nations Econ. Commission Eur., Geneva, Switzerland, Feb. 2020.
- [114] A. Waxman *et al.*, "A visual navigation system for autonomous land vehicles," *IEEE J. Robot. Autom.*, vol. RS-3, no. 2, pp. 124–141, Apr. 1987.
- [115] F. Jurie, P. Martinet, and J. Gallice, "A global road scene analysis system for autonomous vehicles," *IFAC Proc. Volumes*, vol. 28, no. 11, pp. 19–24, Jun. 1995.
- [116] CleanTechnica. (2018). *Uber Reduced LiDAR Array in Self-Driving Cars From 7 Units to 1 in 2016, Creating Pedestrian Blindspots*. [Online]. Available: <https://cutt.ly/4jUvgtT>
- [117] M. Bijelic, T. Gruber, and W. Ritter, "Benchmarking image sensors under adverse weather conditions for autonomous driving," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2018, pp. 1773–1779.
- [118] M. Kutila, P. Pykönen, W. Ritter, O. Sawade, and B. Schäufole, "Automotive LIDAR sensor development scenarios for harsh weather conditions," in *Proc. IEEE 19th Int. Conf. Intell. Transp. Syst. (ITSC)*, Nov. 2016, pp. 265–270.
- [119] D. G. Lowe, "Distinctive image features from scale-invariant keypoints," *Int. J. Comput. Vis.*, vol. 60, no. 2, pp. 91–110, Mar. 2004.
- [120] N. Dalal and B. Triggs, "Histograms of oriented gradients for human detection," in *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit. (CVPR)*, vol. 1, Jun. 2005, pp. 886–893.
- [121] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, "Gradient-based learning applied to document recognition," *Proc. IEEE*, vol. 86, no. 11, pp. 2278–2324, Nov. 1998.
- [122] L. Zhang, L. Lin, X. Liang, and K. He, "Is faster R-CNN doing well for pedestrian detection?" in *Proc. Eur. Conf. Comput. Vis. Cham, Switzerland: Springer*, 2016, pp. 443–457.
- [123] S. Y. Nikouei, Y. Chen, S. Song, R. Xu, B.-Y. Choi, and T. R. Faughnan, "Real-time human detection as an edge service enabled by a lightweight CNN," in *Proc. IEEE Int. Conf. Edge Comput. (EDGE)*, Jul. 2018, pp. 125–129.
- [124] J. Redmon and A. Farhadi, "YOLO9000: Better, faster, stronger," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jul. 2017, pp. 7263–7271.
- [125] L. Heng *et al.*, "Project AutoVision: Localization and 3D scene perception for an autonomous vehicle with a multi-camera system," in *Proc. Int. Conf. Robot. Autom. (ICRA)*, May 2019, pp. 4695–4702.



- [126] A. Kuramoto, M. A. Aldibaja, R. Yanase, J. Kameyama, K. Yoneda, and N. Suganuma, "Mono-camera based 3D object tracking strategy for autonomous vehicles," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2018, pp. 459–464.
- [127] H. Kyutoku, Y. Kawanishi, D. Deguchi, I. Ide, and H. Murase, "Vehicle ego-localization with a monocular camera using epipolar geometry constraints," in *Vehicles, Drivers, and Safety*, vol. 2. Berlin, Germany: De Gruyter, 2020, p. 251.
- [128] Y. Lu, J. Huang, Y.-T. Chen, and B. Heisele, "Monocular localization in urban environments using road markings," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2017, pp. 468–474.
- [129] N. Kemsaram, A. Das, and G. Dubbelman, "A stereo perception framework for autonomous vehicles," in *Proc. IEEE 91st Veh. Technol. Conf. (VTC-Spring)*, May 2020, pp. 1–6.
- [130] I. Bilik, O. Longman, S. Villeval, and J. Tabrikian, "The rise of radar for autonomous vehicles: Signal processing solutions and future research directions," *IEEE Signal Process. Mag.*, vol. 36, no. 5, pp. 20–31, Sep. 2019.
- [131] B. P. Ginsburg *et al.*, "A multimode 76-to-81GHz automotive radar transceiver with autonomous monitoring," in *IEEE Int. Solid-State Circuits Conf. (ISSCC) Dig. Tech. Papers*, Feb. 2018, pp. 158–160.
- [132] A. Stateczny, W. Kazimierski, D. Gronska-Sledz, and W. Motyl, "The empirical application of automotive 3D radar sensor for target detection for an autonomous surface vehicle's navigation," *Remote Sens.*, vol. 11, no. 10, p. 1156, May 2019.
- [133] M. Stolz, E. Schubert, F. Meinel, M. Kunert, and W. Menzel, "Multi-target reflection point model of cyclists for automotive radar," in *Proc. Eur. Radar Conf. (EURAD)*, Oct. 2017, pp. 94–97.
- [134] R. Nabati and H. Qi, "RRPN: Radar region proposal network for object detection in autonomous vehicles," in *Proc. IEEE Int. Conf. Image Process. (ICIP)*, Sep. 2019, pp. 3093–3097.
- [135] A. Bartsch, F. Fitzek, and R. H. Rasshofer, "Pedestrian recognition using automotive radar sensors," *Adv. Radio Sci.*, vol. 10, pp. 45–55, Sep. 2012.
- [136] D. Ma, N. Shlezinger, T. Huang, Y. Liu, and Y. C. Eldar, "Joint radar-communications strategies for autonomous vehicles," 2019, *arXiv:1909.01729*.
- [137] D. S. Hall, "High definition LiDAR system," U.S. Patent 7969558, Jun. 28, 2011.
- [138] H. Wang, B. Wang, B. Liu, X. Meng, and G. Yang, "Pedestrian recognition and tracking using 3D LiDAR for autonomous vehicle," *Robot. Auton. Syst.*, vol. 88, pp. 71–78, Feb. 2017.
- [139] P. J. Navarro, C. Fernandez, R. Borraz, and D. Alonso, "A machine learning approach to pedestrian detection for autonomous vehicles using high-definition 3D range data," *Sensors*, vol. 17, no. 1, p. 18, 2017.
- [140] D. Göhring, M. Wang, M. Schnürmacher, and T. Ganjineh, "Radar/LiDAR sensor fusion for car-following on highways," in *Proc. 5th Int. Conf. Autom., Robot. Appl.*, Dec. 2011, pp. 407–412.
- [141] C. Blanc, L. Trassoudaine, and J. Gallice, "EKF and particle filter track-to-track fusion: A quantitative comparison from radar/LiDAR obstacle tracks," in *Proc. 7th Int. Conf. Inf. Fusion*, 2005, p. 7.
- [142] E. Hyun, Y.-S. Jin, and J.-H. Lee, "A pedestrian detection scheme using a coherent phase difference method based on 2D range-Doppler FMCW radar," *Sensors*, vol. 16, no. 1, p. 124, Jan. 2016.
- [143] J. Han, D. Kim, M. Lee, and M. Sunwoo, "Enhanced road boundary and obstacle detection using a downward-looking LiDAR sensor," *IEEE Trans. Veh. Technol.*, vol. 61, no. 3, pp. 971–985, Mar. 2012.
- [144] S. K. Kwon, E. Hyun, J.-H. Lee, J. Lee, and S. H. Son, "Detection scheme for a partially occluded pedestrian based on occluded depth in LiDAR-radar sensor fusion," *Proc. SPIE*, vol. 56, no. 11, 2017, Art. no. 113112.
- [145] Y. Wang, W.-L. Chao, D. Garg, B. Hariharan, M. Campbell, and K. Q. Weinberger, "Pseudo-LiDAR from visual depth estimation: Bridging the gap in 3D object detection for autonomous driving," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2019, pp. 8445–8453.
- [146] L. Hobert, A. Festag, I. Llatser, L. Altomare, F. Visintainer, and A. Kovacs, "Enhancements of V2X communication in support of cooperative autonomous driving," *IEEE Commun. Mag.*, vol. 53, no. 12, pp. 64–70, Dec. 2015.
- [147] W. G. Najm *et al.*, "Frequency of target crashes for intelligidrive safety systems," Nat. Highway Traffic Saf. Admin., Washington, DC, USA, Tech. Rep. DOT HS 811 381, 2010.
- [148] J. Maddox, P. Sweatman, and J. Sayer, "Intelligent vehicles + infrastructure to address transportation problems—A strategic approach," in *Proc. 24th Int. Tech. Conf. Enhanced Saf. Vehicles (ESV)*, 2015, pp. 1–12.
- [149] R. Hult, G. R. Campos, E. Steinmetz, L. Hammarstrand, P. Falcone, and H. Wymeersch, "Coordination of cooperative autonomous vehicles: Toward safer and more efficient road transportation," *IEEE Signal Process. Mag.*, vol. 33, no. 6, pp. 74–84, Nov. 2016.
- [150] U.S. Department of Transportation NHTSA. (2017). *Traffic Safety Facts Annual Report Tables*. [Online]. Available: <https://cdn.nhtsa.gov/tsf/tables/tsfar.htm#>
- [151] M. Zhou, X. Qu, and S. Jin, "On the impact of cooperative autonomous vehicles in improving freeway merging: A modified intelligent driver model-based approach," *IEEE Trans. Intell. Transp. Syst.*, vol. 18, no. 6, pp. 1422–1428, Jun. 2017.
- [152] S. A. Bagloee, M. Taviana, M. Asadi, and T. Oliver, "Autonomous vehicles: Challenges, opportunities, and future implications for transportation policies," *J. Mod. Transp.*, vol. 24, no. 4, pp. 284–303, Dec. 2016.
- [153] J. M. Anderson, K. Nidhi, K. D. Stanley, P. Sorensen, C. Samaras, and O. A. Oluwatola, *Autonomous Vehicle Technology: A Guide for Policymakers*. Santa Monica, CA, USA: Rand Corporation, 2014.
- [154] Q. Jin, G. Wu, K. Boriboonsomsin, and M. Barth, "Advanced intersection management for connected vehicles using a multi-agent systems approach," in *Proc. IEEE Intell. Vehicles Symp.*, Jun. 2012, pp. 932–937.
- [155] U. P. Mudalige, "Fail-safe speed profiles for cooperative autonomous vehicles," U.S. Patent 8676466, Mar. 18, 2014.
- [156] J. Nie, J. Zhang, W. Ding, X. Wan, X. Chen, and B. Ran, "Decentralized cooperative lane-changing decision-making for connected autonomous vehicles," *IEEE Access*, vol. 4, pp. 9413–9420, 2016.
- [157] S.-W. Kim *et al.*, "Cooperative perception for autonomous vehicle control on the road: Motivation and experimental results," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, Nov. 2013, pp. 5059–5066.
- [158] S.-W. Kim, W. Liu, M. H. Ang, E. Frazzoli, and D. Rus, "The impact of cooperative perception on decision making and planning of autonomous vehicles," *IEEE Intell. Transp. Syst. Mag.*, vol. 7, no. 3, pp. 39–50, Fall 2015.
- [159] H. Farah, H. N. Koutsopoulos, M. Saifuzzaman, R. Kölbl, S. Fuchs, and D. Bankosegger, "Evaluation of the effect of cooperative infrastructure-to-vehicle systems on driver behavior," *Transp. Res. C, Emerg. Technol.*, vol. 21, no. 1, pp. 42–56, Apr. 2012.
- [160] I. V. Gritsuk *et al.*, "Information model of V2I system of the vehicle technical condition remote monitoring and control in operation conditions," SAE Tech. Paper 2018-01-0024, 2018.
- [161] M. S. Kristoffersen, J. V. Dueholm, R. Gade, and T. B. Moeslund, "Pedestrian counting with occlusion handling using stereo thermal cameras," *Sensors*, vol. 16, no. 1, p. 62, 2016.
- [162] J. Wang, Y. Gao, Z. K. Li, X. L. Meng, and C. M. Hancock, "A tightly-coupled GPS/INS/UWB cooperative positioning sensors system supported by V2I communication," *Sensors*, vol. 16, no. 7, p. 944, 2016.
- [163] A. Fascista, G. Ciccicarese, G. Ricci, and A. Coluccia, "A localization algorithm based on V2I communications and AOA estimation," *IEEE Signal Process. Lett.*, vol. 24, no. 1, pp. 126–130, Jan. 2017.
- [164] D. G. Perumal, B. Subathra, G. Saravanakumar, and S. Srinivasan, "Extended Kalman filter based path-planning algorithm for autonomous vehicles with I2V communication," *IFAC-PapersOnLine*, vol. 49, no. 1, pp. 652–657, 2016.
- [165] O. Grembek, A. Kurzhanskiy, A. Medury, P. Varaiya, and M. Yu, "Making intersections safer with I2V communication," *Transp. Res. C, Emerg. Technol.*, vol. 102, pp. 396–410, May 2019.
- [166] P. K. Singh, S. Sharma, S. K. Nandi, and S. Nandi, "Multipath TCP for V2I communication in SDN controlled small cell deployment of smart city," *Veh. Commun.*, vol. 15, pp. 1–15, Jan. 2019.
- [167] O. Senouci, Z. Aliouat, and S. Harous, "MCA-V2I: A multi-hop clustering approach over vehicle-to-internet communication for improving VANETs performances," *Future Gener. Comput. Syst.*, vol. 96, no. 1, pp. 309–323, Jul. 2019.
- [168] F. Jameel, M. A. Javed, and D. T. Ngo, "Performance analysis of cooperative V2V and V2I communications under correlated fading," *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 8, pp. 3476–3484, Aug. 2020.
- [169] A. Rasouli and J. K. Tsotsos, "Autonomous vehicles that interact with pedestrians: A survey of theory and practice," *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 3, pp. 900–918, Mar. 2019.

- [170] A. Habibovic, J. Andersson, V. M. Lundgren, M. Klingegård, C. Englund, and S. Larsson, "External vehicle interfaces for communication with other road users?" in *Road Vehicle Automation 5*. Cham, Switzerland: Springer, 2019, pp. 91–102.
- [171] D. Dey and J. Terken, "Pedestrian interaction with vehicles: Roles of explicit and implicit communication," in *Proc. 9th Int. Conf. Automot. User Interfaces Interact. Veh. Appl.*, Sep. 2017, pp. 109–113.
- [172] D. Dey, M. Martens, C. Wang, F. Ros, and J. Terken, "Interface concepts for intent communication from autonomous vehicles to vulnerable road users," in *Proc. Adjunct Proc. 10th Int. Conf. Automot. User Interfaces Interact. Veh. Appl.*, Sep. 2018, pp. 82–86.
- [173] P. Bazilinskyy, D. Dodou, and J. de Winter, "Survey on eHMI concepts: The effect of text, color, and perspective," *Transp. Res. F, Traffic Psychol. Behav.*, vol. 67, pp. 175–194, Nov. 2019.
- [174] K. Mahadevan, S. Somanath, and E. Sharlin, "Communicating awareness and intent in autonomous vehicle-pedestrian interaction," in *Proc. CHI Conf. Hum. Factors Comput. Syst.*, Apr. 2018, pp. 1–12.
- [175] Car Connectivity Consortium. (2020). *Home Page*. [Online]. Available: <https://www.car-2-car.org/>
- [176] S. M. Iranmanesh, E. Moradi-Pari, Y. P. Fallah, S. Das, and M. Rizwan, "Robustness of cooperative forward collision warning systems to communication uncertainty," in *Proc. Annu. IEEE Syst. Conf. (SysCon)*, Apr. 2016, pp. 1–7.
- [177] M. Amoozadeh *et al.*, "Security vulnerabilities of connected vehicle streams and their impact on cooperative driving," *IEEE Commun. Mag.*, vol. 53, no. 6, pp. 126–132, Jun. 2015.
- [178] *Projected Number of Autonomous Cars Globally From 2019 to 2024*. Accessed: May 3, 2021. [Online]. Available: <https://www.statista.com/statistics/1230664/projected-number-autonomous-cars-worldwide/>
- [179] Connected Automated Driving. (2021). *2021 Gaps and Recommendations*. [Online]. Available: <https://www.connectedautomateddriving.eu/standards/2021-gaps-and-recommendations/>
- [180] F. Khan, R. L. Kumar, S. Kadry, Y. Nam, and M. N. Meqdad, "Autonomous vehicles: A study of implementation and security," *Int. J. Electr. Comput. Eng.*, vol. 11, no. 4, p. 3013, Aug. 2021.
- [181] J. Hecht, "LiDAR for self-driving cars," *Opt. Photon. News*, vol. 29, no. 1, pp. 26–33, 2018.
- [182] J. Fang *et al.*, "Augmented LiDAR simulator for autonomous driving," *IEEE Robot. Autom. Lett.*, vol. 5, no. 2, pp. 1931–1938, Apr. 2020.
- [183] G. Calleja-Sanz, J. Olivella-Nadal, and F. Solé-Parellada, "Technology forecasting: Recent trends and new methods," in *Research Methodology in Management and Industrial Engineering*. Bristol, U.K.: IOP, 2020, pp. 45–69.
- [184] M. Popescu, "Analysing trends and correlations from internet searches: Case study of Romania," *Annales Univ. Apulensis, Ser. Oeconomica*, vol. 19, no. 1, pp. 82–86, 2017.
- [185] H. Choi and H. Varian, "Predicting the present with Google trends," *Econ. Rec.*, vol. 88, no. 1, pp. 2–9, 2012.
- [186] H. A. Carneiro and E. Mylonakis, "Google trends: A web-based tool for real-time surveillance of disease outbreaks," *Clin. Infectious Diseases*, vol. 49, no. 10, pp. 1557–1564, Nov. 2009.
- [187] N. Nedjah and L. S. Junior, "Review of methodologies and tasks in swarm robotics towards standardization," *Swarm Evol. Comput.*, vol. 50, Nov. 2019, Art. no. 100565.
- [188] G. Biggi and J. Stilgoe, "Artificial intelligence in self-driving cars research and innovation: A scientometric and bibliometric analysis," *Social Sci. Res. Netw., Tech. Rep.* 3829897, 2021.



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