Highly Automated Vehicles and Self-Driving Cars

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Self-driving cars have, in recent years, clearly become among the most actively discussed and researched topics. By all definitions, these systems, as a third robotic revolution, belong to the robotics field, despite the fact that people generally assign them to a specific domain of the automotive industry [1]. Replicating the complex task of human driving by an autonomous system poses countless engineering challenges, involving the wider field of robotics, including environment perception, decision making, and control.

Whereas most of today's prototypes are able to achieve certain functionalities, self-driving vehicles—as consumer products—are still several years away from mass production, primarily due to the strict and constantly evolving regulations and testing protocols required of traditional automotive companies. Until then, new functionalities will continue to be introduced to vehicles gradually, requiring human supervision and effective human–robot cooperation through sophisticated interfaces.

There are many predictions about how self-driving cars will change our lives, based approaches from both the philosophical and scientific points of view. Contemporary society is characterized by mobility, with cars playing a significant role; approximately 1 billion units are in use worldwide. According to experts, equipping these vehicles with intelligent driver assistance or completely autonomous functionalities will ultimately lead to a 90% drop in road accident rates, a 60% reduction of carbon-dioxide emissions (due to efficient trajectory planning), and savings of more than 1 billion h per day for commuters around the world [2].

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Industry Tutorials—Why Should You Care?

The Industrial Activities Board of the IEEE Robotics and Automation Society has established an industry tutorial column in *IEEE Robotics and Automation Magazine*, where key topical areas of robotics are introduced to the community in a practical manner. Articles focus on the history, achievements, and future potential of the fields of robotics, including business aspects and the standardization landscape. These short articles aim to provide a better understanding of the rapidly evolving ecosystem, starting with autonomous vehicles and medical robotics, and moving on to rescue robotics, autonomous underwater vehicles, and unmanned aerial vehicles. If you have any comments or are willing to contribute, let us know at ras-iab@ieee.org.

Brief History of Self-Driving

The first concept of self-driving cars was introduced in the 1920s; instead of computer-controlled vehicles, however, the Pontiac Phantom cars were remotely controlled, demonstrating the power of radio communication. A self-driving concept car, a General Motors Firebird IV, was presented at the 1964 New York World's Fair. The first computer-controlled self-driving vehicle—created by Carnegie Mellon University (CMU) and introduced in the mid-1980s under the name *Navlab 1*—was capable of routing and obstacle avoidance.

The first pan-European initiative for self-driving development was carried out within the scope of the Eureka Programme for a European Traffic of Highest Efficiency and Unprecedented Safety Project, an eight-year-long joint effort involving universities and auto manufacturers to define state-of-the-art self-driving functionalities. The project was successfully concluded in 1995, and the prototype cars demonstrated lane keeping, cooperative driving, automated intelligent cruise control, and enhanced vision capabilities— functionalities we find in today's production vehicles.

The industry has quickly recognized the potential of automated systems in logistics, and automated guided vehicles first appeared in well-controlled factory environments in the 1950s. Given these environments, with known pathways and clear ground, a US$2 billion global business has developed that grows 10% annually. The technology received considerable public attention when Amazon began using machines made by Kiva, the robotics company it acquired for US$775 million in 2012. Today, systems like KUKA's KMP 1500 freely roam the shop floor, relying on omnidirectional drive technologies with mecanum wheels and positioning payloads up to 1,500 kg with millimeter accuracy. The largest autonomous platforms (e.g., the KUKA omniMove) can carry whole airplanes or concrete bridge parts that are still in production; flexible manufacturing concepts such as a matrix body shop no longer belong in the domain of science fiction. Nevertheless, the real challenges of the field started when the robots were let out of the factories.

The U.S. Defense Advanced Research Projects Agency (DARPA) Grand Challenge series is one of the most notable autonomous vehicle contests of the 2000s, representing the first long-distance competition for driverless cars and facilitating robotic development of unmanned military ground vehicles. The first two challenges took place in the Mojave Desert; the third, the DARPA Urban Challenge, required navigation, negotiation, and scenario-handling in urban environments as well (at an abandoned Air Force base in Southern California). Whereas these vehicles were custom-designed for the specific environment and tasks, countless best-practices and yet-unknown challenges have been published on the topics of perception, decision making, and high-speed vehicle control, some that are still used as a useful guide in self-driving development. The top vehicles were equipped with multiple lidar sensors and high-precision global positioning system receivers, using camera vision as secondary information—an approach that was taken on by many of today's research teams as a heritage from DARPA Grand Challenges.

However, Stanley, the 2005 winner from Stanford University, also used machine learning techniques for obstacle detection, forecasting the new era of self-driving car development. This was also the first public appearance of these technologies as a potential megatrend, because the best car of the 2004 challenge, the CMU Red Team, could accomplish only 5% of the race route; in 2005, five teams completed the route. This focused significant attention on the domain, so, after 2007, DARPA gave up with this series, because it had become too easy for state-of-the-art systems.

Meanwhile, Google was the first to invest big on this technology, beginning with the Stanford team behind Stanley. Google began operation in its X division in 2009 with retrofitted Toyota Prius models; in 2011, the state of Nevada gave permits for the first public road testing. It was Google's own developed self-driving car that claimed the first fully driverless ride on public roads in 2015. Google has kept its confidence in lidar; in late 2016, the technology was spun off to Waymo, which promises to start offering public service very soon.

With the increasing computational efficiency in image data processing and sophisticated algorithms, vision is slowly taking over the role of primary sensors in self-driving cars. Many of today's advanced functionalities, such as lane keeping or pedestrian detection, are solved by the use of cameras. In production vehicles, these functionalities rely on traditional computer vision algorithms, whereas research communities and progressive technology companies are migrating to deep learning (DL) techniques using neural network (NN) architectures.

To define current capabilities of autonomous vehicles and provide a harmonized classification system and supporting definitions, the Society of Automotive Engineers defined six levels of autonomy within the scope of the standard *Taxonomy and Definitions for Terms Related to On-Road Motor Vehicle Automated Driving Systems* [3]:

- *L0*: no automation
- *L1—driver assistance*: specific functions under control
- *L2—partial automation*: combined function automation (e.g., adaptive cruise control)
- *L3—conditional automation*: automation of all critical functions with limitations (limited self-driving); the driver must be able to take control at all times
- *L4—high automation*: the vehicle performs all driving tasks under certain conditions; the driver may take control
- *L5—full automation*: the vehicle performs all driving tasks under all conditions; driver may take control.

Due to its consistency for industrial practice and steplike progression through the levels, this definition is widely accepted and applied by both the academic and industrial communities. Levels 0–2 refer to advanced driver assistance systems (ADAS), where the human driver monitors *and* performs the dynamic driving task (decision making and maneuver execution), whereas levels 3–5 require the system to monitor the environment actively and carry out these tasks.

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Although strict boundaries cannot be defined from the technological point of view, as a rule of thumb, levels 0–2 can be solved by traditional sensor-processing algorithms with currently available hardware processors and, thus, can be found in most of today's production vehicles. Levels 3–5, on the other hand, refer to variants of hands-off driving, where the use of advanced machine learning and DL techniques is essential. The complex task of coordinating the sensing–planning–control chain requires a general, integrated approach, where the individual development of ADAS functions is just a small portion of the big picture.

The human factor introduces another issue: due to the relatively high level of automation, drivers tend to become distracted and bored and look for other activities. The main problem is that humans are not efficient in long, inactive monitoring-type tasks, and drivers usually overtrust the system [4].

Components of Self-Driving Development

The road to fully autonomous, L5 self-driving cars leads through a structured development process, where one needs adequate tools, algorithms, and processing hardware to test and deploy these systems:

1) *algorithms*: integration of the building blocks in an independent self-driving full-stack software, accounting for sensor handling, data processing, perception, localization, decision making, and control
2) *development tools*: off-line software tools for data handling; a training framework for artificial intelligence (AI)-based algorithms, testing, verification, and maintenance
3) *hardware*: a high-performance, low-power automotive-grade processor, allowing low-level optimization of algorithms, with specialized architectures for NN calculations (inference).

Algorithms

The role of sophisticated algorithms in solving the three main tasks of self-driving (perception, localization, and planning) is to find the right balance between traditional and AI-based algorithms. It is widely accepted that AI will be the driving force behind the software, although the specific role of machine intelligence and the point of deployment occupy a wide spectrum, depending on the approach used [5]. One of these is the application of end-to-end black-box learning by observation; here, the car learns how to navigate, negotiate, and adjust control signals solely by observing human drivers.

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Although promising results have been achieved in simulated environments (for which computer games provide an efficient development platform), the limited system transparency leads to difficult fault tracing, and testing the system for every case is nearly impossible. A more robust but significantly more complex way is to analyze human driving and define the building blocks of a self-driving software. These blocks have a hierarchic relation and are intended to aid the main task by providing information about the environment, the vehicle–environment interaction, and an optimal trajectory to be executed:

- *perception*: low- and high-level sensor fusion (information integration), object detection and classification, and abstract environment reconstruction
- *localization*: global localization and routing, mapping, odometry, and local positioning
- *planning*: scenario interpretation, tracking and prediction, motion (maneuver) planning, local trajectory planning, and actuator control.

Development Tools

In the automotive industry supply chain, car manufacturers (as original equipment manufacturers) play a significant role in component integration, building individual and independent components into the final system. These are usually provided by first-level automotive suppliers, resulting in a largely distributed platform in terms of functionality. Future cars will not have the luxury of this type of distribution, because all components will need to function in harmony, progressing toward a centralized processing architecture. As a natural consequence, the simultaneous development of components and their constant cross testing is becoming an integral part of self-driving development, where custom off-line development tools provide a platform for the following:

- *data handling*: data collection, annotation (labeling), generation and enhancement, pre- and postprocessing, and sensor calibration
- *algorithm support*: a flexible training environment for AI algorithms and frameworks for NN inference optimization and high-level sensor fusion (the association of various sensor data to real-world instances)
- *testing*: algorithm verification (precision, recall, false rejection), benchmarking and metrics development, and complex off-line simulation.

Processing Hardware

Although the performance of the algorithms is low-bounded by their minimally required reliability factors, the available processing power poses another challenge and an upper bound to complexity, which, in the case of massive use of AI-based algorithms, mainly affects the inference of NNs. In the case of convolutional NNs (CNNs), one of the most efficient DL approaches, this limits the number and size of layers, creating a need for optimized network architectures and relying on today's vast state-of-the-art networks. Now, general-purpose computing on graphics processing units (GPUs) is a standard way of training and inferencing NNs for sensor data processing and decision making, taking advantage of optimized inference engines for massively parallel GPU computation. However, GPUs, as general-purpose computing units, have been primarily optimized for pixel-by-pixel computations on graphics engines, making them suboptimal for processing CNNs per se. This fact has initiated a new era of hardware development, with chip design increasingly being focused on hardware acceleration of NN inference, increasing the performance density of these processing units, and, due to their predicted heavy use in the automotive industry, allowing automotive safety integrity-level compliance. This explains the great interest of chip manufacturers in this domain.

Sensors on Self-Driving Cars

Owing to the large variety of off-the-shelf sensors available, there are no identical prototype platforms among research communities and industrial/technological companies. Furthermore, the choice of sensors affects the hierarchy and fusion of algorithms, and vice versa: a structured approach will determine the position and type of sensors placed around the vehicle. Cameras with different fields of view, lidar units, radars, and ultrasonic sensors are often considered essential. Some of these might play the role of primary sensors, often completely taking over the role of other sensors.

This has resulted in a segmentation, with the developer community taking either the camera-first approach (companies like Tesla, Mobileye, and AImotive) or the lidar-first approach (utilized by Waymo–Google, Uber, and Drive.ai). Using cameras as primary sensors allows one to mimic the human driver in perception and localization tasks, as drivers rely on vision 99% of the time they spend driving. With a sufficient number of cameras and the proper choice of algorithms, the type, distance, size, and orientation of objects and landmarks can be extracted, with radar or ultrasonic sensors taking the place of the still-expensive lidar sensors in distance measurement. However, cameras require large processing power and are significantly exposed to light conditions and environmental changes, requiring diverse training data for AI-based image processing algorithms.

Using lidars as primary sensors, the task of localization becomes easier, matching the point cloud of the raw sensor output to a prerecorded, three-dimensional, high-definition (HD) map on multiple layers. This, however, requires an up-to-date HD map of the world, working reliably in environments that lack quality landmarks or features to be matched by the lidar (typically highways or rural roads), which calls into question the scalability of the lidar-first approach. This explains Google's and other companies' huge investments into creating highly accurate maps. Furthermore, the high cost of current lidar sensors slows down their deployment into production vehicles, although solid-state lidars with no moving parts are predicted to penetrate the market soon.

Controlling the Vehicle

The prototype vehicle platform largely influences the choice of sensor setup, the computing hardware, and the actuator control parameters. To some extent, a recalibration of the sensors and on-the-fly calibration methods can bridge these challenges. However, a thorough testing of the whole integrated system requires a platform-agnostic, drive-by-wire solution that communicates with the self-driving software and the controller area network (CAN) bus, which forwards commands and receives actuator states. The original role of the CAN bus standard was to allow communication between distributed devices and microcontrollers on a message-based protocol. Some organizations provide drive-by-wire solutions only on specific platforms, and others can convert virtually any car model into such a system, providing custom application programming interfaces. However, due to standardized message-based communication, it is not unusual to convert nonstandard vehicles to self-driving cars by reverse-engineering methods.

Once the software can send control messages and receive the vehicle's state from both external sensors (cameras, radars, lidar, and so forth) and internal devices through the CAN interface, the desired trajectory can be executed. Due to the wide range of speed and acceleration values applied, the highly nonlinear behavior during steering, and the often unmodeled lateral dynamics, a large variety of actuator control approaches has been applied both for steering and acceleration control. These include finely tuned proportional–integral–derivative controllers, model predictive control, fuzzy control, and even neural control, such as system dynamics identification based on NNs. Generally speaking, the overall robustness and performance of trajectory tracking is a function of detection accuracy and stability, decision making, and trajectory planning smoothness; performance requirements, on the other hand, are usually set for a specific use case by automotive standards [5].

Open-Source Platforms

The development of self-driving technology is undoubtedly a costly procedure: for a full prototype system, one needs to account for vehicle platforms, high-end processors, and quality sensors. However, L5 automation has not yet reached the product development stage, and there is room for research activities from independent developers and organizations on even the most fundamental topics.

One of the most popular platforms has been initiated by Udacity [16]: building an open-source self-driving car, breaking down the problem into multiple complex challenges, and offering a competition to teams running their solutions on this prototype vehicle. Furthermore, Udacity launched a self-driving car engineer nanodegree, covering state-of-the-art topics in self-driving, heavily aided by machine intelligence.

The Open Source Self-Driving Car Initiative [17] is an active community of software developers, sharing repositories for solving subtasks of self-driving. Advanced open-source frameworks for complex software stacks have recently been released (or announced) by former and current competitors in the self-driving car development race, including Comma.ai and Baidu, to help others in the industry, particularly car manufacturers, develop autonomous vehicles.

Real-world testing of self-driving platforms is often challenging.

Real-world testing of self-driving platforms is often challenging due to constantly developing testing regulations and the difficulty of scenario generation and reproduction. Many players in the field are developing a virtual test environment in simulation engines that satisfies the compatibility requirements of software frameworks. Computer games including diverse scenarios and high-quality graphics serve as an alternative development platform. The DeepDrive project [18] was recently open-sourced by OpenAI, repurposing the popular computer game *Grand Theft Auto* as a self-driving car simulator, providing pretrained self-driving agents and data sets. Similarly, the Open Racing Car Simulator [19] provides a highly customizable research platform capable of integrating custom vehicle and object dynamics with scenario generation.

On the algorithm level, open-source libraries for C/C++ languages offer robust algorithms, such as the ones offered by OpenCV, addressing many tasks related to perception and localization based on visual data. These codes are released under a license such that both academic and commercial use are supported. For advanced algorithms utilizing NNs of any type, countless frameworks are available, providing precoded network architectures as building blocks, widely used solvers and cost functions, full architecture examples, and references to publicly available training data sets. These frameworks (among the most popular are Caffe, Theano, Torch, and TensorFlow) generally support fully connected, convolutional, and even recurrent NN architectures.

Society demands an understanding of the operation principles and consequences of an increased number of self-driving vehicles on the road.

Besides open-source software tools, open standards are also emerging in optimized hardware development. Today, most NN tool kits, frameworks, and inference engines use proprietary formats to describe the trained network architecture and parameters. As a consequence, many proprietary importers need not be constructed to enable a trained network to be executed across multiple hardware platforms. The Khronos Neural Network Exchange Format [20], originally initiated by AImotive, is designed to simplify creating a network and running the trained network on other tool kits or inference engines. The standard was released in August 2018, and it is expected to reduce deployment friction and create a bridge for cross-platform DL tools, engines, and applications.

Safety

Safety has been an intensively researched topic for automated vehicles, as the projected complexity of self-driving capabilities extends to traditional safety assessment methods. Current validation and verification tools include safety standards applied to specific components or driver assistance features of the car, assuming that vehicle control is overseen by the human driver. Systems, such as collision mitigation systems (CMSs) or lane-keep assist, used to be tested and verified according to established pipelines or processes, such as the automotive standard V-model or International Organization for Standardization (ISO) 26262 [6]. However, in the case of CMS, false-detection filtering and avoiding unintended braking are properties addressed by the newly developed *Road Vehicles—Safety of the Intended Functionality* standard [7]. Highly automated systems will require full assessment of their performance and a safe development pipeline to verify their readiness for the cluttered human environment [8]. Simulation as an automotive tool for test and development is recognized and discussed in detail in some recent works.

One of the most important statements of the Vienna Convention (ratified in 1968 by 74 countries, excepting the United States) is that the human driver is liable for accidents caused with the vehicle, taking full responsibility. This is primarily due to the lack of existing test procedures for L2+ self-driving systems.

Figure 1 presents a safety development workflow that rethinks traditional automotive product development techniques regarding system design, software and hardware design, and integration. Laws and standards serve as boundary conditions/inputs for the

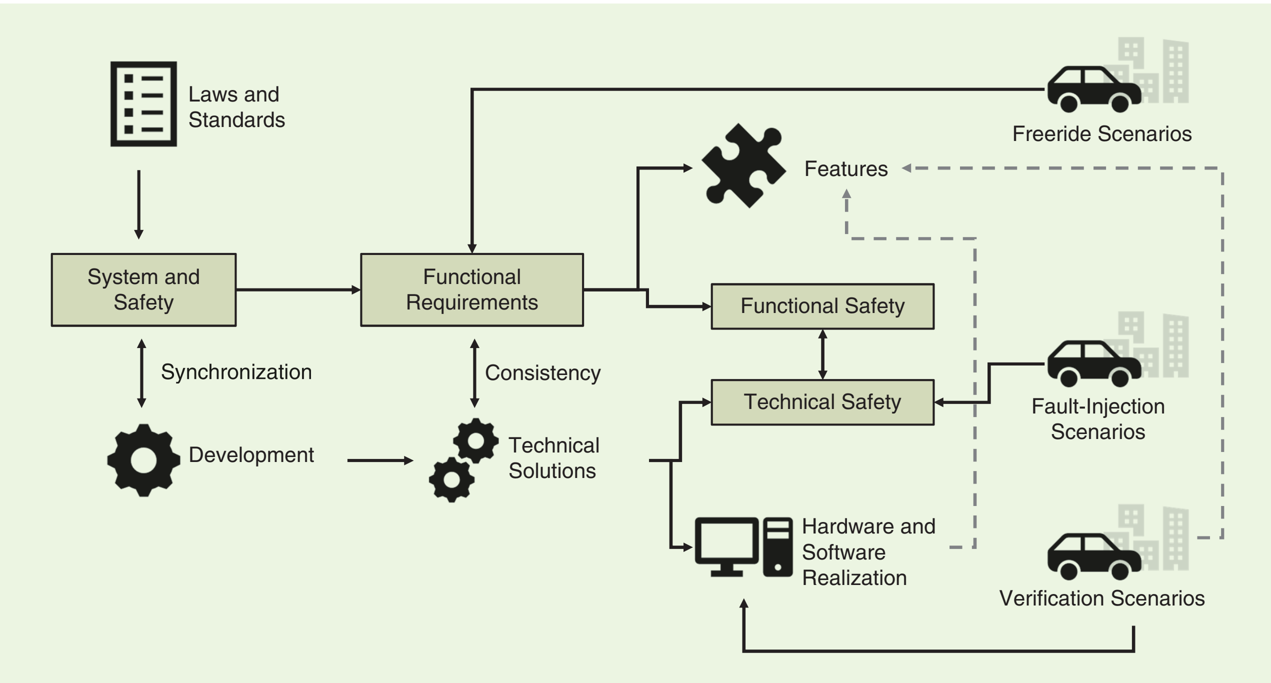

Figure 1. An alternative safety-development workflow that better fits the extended requirements of highly autonomous cars.

safety development pipeline, as presented by Takacs et al. [9].

Ethics and Social Questions

As the enabling technologies of self-driving are being developed, society demands an understanding of the operation principles and consequences of an increased number of self-driving vehicles on the road. Although AI has been a tool used for some years now in diagnostics, forecasting, and decision making for many professional fields (including finance, advertising, and economics), self-driving cars may become the first safety-critical system that will have a worldwide effect on society. It is a challenging task to forecast what direct social impacts we are going to experience once self-driving vehicles become an integral part of our lives; it is even more difficult to address indirect consequences brought about through such ideas as car sharing, transforming our commute time to more efficient working time, and changing urban layouts [10].

Even though self-driving cars will increase road safety and provide a significant decrease in road injuries (there were 1.26 million reported fatalities in 2015), an intense ethical discussion on the self-driving car's moral decision making has been going on recently. This will require an educated public discourse, sparked by such promising initiatives as the Robotic and AI Governance Initiative [11], leading to an ethical code of conduct or robot manifesto [12]. Many of these discussions can be traced back to the classic trolley problem, where an ethical decision has to be made concerning whether to switch tracks of a runaway trolley to sacrifice one life in exchange for five other lives. The Massachusetts Institute of Technology (MIT) projected this problem to the decision making of self-driving cars.

The MIT Moral Machine [21] generates moral dilemmas and collects information on the choices participating volunteers make between destructive outcomes. The generality of these problems can be illustrated by the fact that a variant of the ethics guidelines used in medicine—deontology and utilitarianism—can be observed in the case of self-driving cars as well, with either a society-centered or individual-centered approach being taken. Although some of today's car manufacturers have already taken a stand on one side or the other (e.g., Mercedes–Benz will always prioritize to protect its passengers), currently there is no technological evidence that AI in self-driving vehicles would be forced to make such decisions, whether inherently based on software architecture or learned via training methods. This allows engineers to approach the problem of self-driving primarily from the functionality side, which will ultimately lead to better road safety and more efficient mobility.

The need for safety has been broadly recognized by the engineering community, and thus IEEE called to action the Global Initiative on Ethics of Autonomous and Intelligent Systems, which aims to support safe autonomous system development via ethical standards (the P7000 standard series) [13]. To overcome the compatibility challenges involved in applying traditional processes to the higher level of autonomy, automotive safety is on a path to integration into the technology development workflow from the concept level all the way to testing and validation.

Standardization and Clearance

Because the whole field is emerging and evolving rapidly, autonomous vehicle technology presents a huge challenge to standardization bodies and legal authorities. The objective assessment and quantification of self-driving algorithms and systems for safety is now the focus of numerous standards developing organizations (SDOs):

- ISO Technical Committee (TC) 022 (Road Vehicles); ISO TC 204 (Intelligent Transport Systems)
- ISO AWI PAS 21448; *Road Vehicles—Safety of the Intended Functionality* (Working Group 08 under the TC 022/Subcommittee 32)
- IEEE 1609.2a-2017, *IEEE Standard for Wireless Access in Vehicular Environments—Security Services for Applications and Management Messages*
- ANSI ITSDF B56.5-2012, *Safety Standard for Driverless, Automatic Guided Industrial Vehicles and Automated Functions of Manned Industrial Vehicles*
- ASTM Committee F45 on Driverless Automatic Guided Industrial Vehicles.

Some of these activities are connected to the ongoing general robot standardization activities of the large SDOs, such as ISO TC299 [14]. Nevertheless, these are all technical standards, aimed at addressing the technical issues listed previously. Another major area for L4 and L5 validation is liability and ethical responsibility. This has much in common with the field of medical robotics, where the increasing level of autonomous functions raised similar concerns [15].

> **Self-driving cars may become the first safety-critical system that will have a worldwide effect on society.**

In current serial-production cars, only ADAS functionalities can be found. From the viewpoint of safety, this defines cooperative driving, i.e., the human and the vehicle handle the driving task together. On the other hand, L3 systems may self-drive in place of the human driver but still not be able to handle complex emergency situations. According to current automotive safety standards, L3 systems must be able to recognize emergency situations where the intended functionality cannot be carried out, shifting the full responsibility back to the human driver. However, this handover process is not yet standardized [8].

Conclusion—Why Should You Care?

The research and development community quickly took on the new challenges presented by self-driving technologies; now, the automotive industry is gradually turning toward autonomous solutions as well. It is big business, as the recent investment stories clearly show: there has been more than US$90 billion invested in the field over the past four years, led by Intel, which bought Mobileye in March 2017 for US$15 billion.

All major car manufacturers announced their L4+ cars slated for the 2019–2020 period, promising full self-driving capabilities by 2025. New schools and engineering programs were launched to feed the needs of this booming industry, and the influx of engineers to the domain created human resources shortages in other areas of robotics.

Autonomous vehicle technology presents a huge challenge to standardization bodies and legal authorities.

As current research shows, there are significant safety issues regarding the transition between autonomous and manual control. These issues currently hinder the introduction of L3 and L4 serial-production autonomous cars, but, at the same time, they accelerate research and innovation toward true self-driving. The age of autonomous vehicles is to come, much sooner than we anticipated.

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