A Survey of Sensor Technologies for Perception in Automated Driving

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***Abstract*—After more than 20 years of research, ADAS are common in modern vehicles vehicles available in the market. Automated Driving systems, still in research phase and limited in their capabilities, are starting early commercial tests in public roads. These systems rely on the information provided by on-board sensors, which allow to describe the state of the vehicle, its environment and other actors. Sensors are the first stage of any automated driving architecture, representing a key factor in the design of the system. This survey reviews existing and upcoming sensor solutions applied to ADAS and Automated Driving, based in both well-known and novel sensing technologies, applied to the most common tasks in perception. They are put in context making a historical review of the most relevant demonstrations on Automated Driving developed by academy and other institutions, focused on their sensing setup. Finally, the article presents a snapshot of the future challenges for sensing technologies and perception, finishing with an overview of the commercial initiatives and manufacturers alliances that will show the intention of the market in sensors technologies for Automated Vehicles.**

***Index Terms*—Automated Driving, sensors, perception, OEM.**

I. Introduction

Every year more than one million people die on road accidents and several million more get injured [1]. In addition to the social cost, it also has an important economic impact for nations worldwide. According to [2] the most frequent causes for car accidents in the European Union are human related: speeding, driving under the effects of alcohol or drugs, reckless driving, distractions or just plain misjudgments. Automated Driving systems, also called self-driving vehicles, aim to take the human driver out of the equation. Thus, they are designed to be a valuable tool towards reducing the number of traffic accidents.

Based on recent developments and demonstrations around the world, there is a tendency to think that Automated Driving with a high level of automation will be available in a few years.

The architecture of autonomous vehicles is usually divided into three categories: perception of the environment, behavior planning and motion execution [3]. Autonomous vehicles obtain information about their surroundings using different sensors, such as cameras, LiDARs and radars. Raw data is processed to extract relevant features which are the input to the following stages (behavior planning and motion execution), that will perform tasks such as path planning, collision avoidance or control of the vehicle among others.

Perception is a very challenging problem for several reasons. First, the environment is complex and highly dynamic, with some cases involving a large number of participants (dense traffic, populated cities). Second, it needs to work reliably under a wide range of external conditions, including lighting and weather (rain, fog, snow, dust). Perception errors are propagated and can cause of severe accidents. Some real examples include the 2016 Tesla AutoPilot accident [4], where a man was killed after its car crashed a truck: the camera failed to detect the gray truck against a bright sky while radar detection was discarded as background noise by perception algorithms. Later in 2018, a Tesla model X crashed a highway divider after the lane following system failed to detect faded lines and the concrete divider was not recognized, killing the driver [5]. Also in 2018, an experimental self-driving Uber vehicle killed a woman crossing the road [6] in the night, dressed in dark clothes. Only the LiDAR provided a positive detection, that was discarded as a false positive by perception algorithms.

This article reviews sensor technologies and perception algorithms, and explores their relation to provide an integral view of the process that leads from raw sensor data to meaningful information for the driving task. This topic has been previously investigated in the literature, but usually centered on ADAS implementation [7], [8] or at a more general level within Automated Driving [9].

The content of the article is organized as follows. Section II describes the sensors commonly used for perception explaining the technologies, drawbacks and advantages, and related emerging technologies that can be used in the future. It also presents a taxonomy of information that allows to link sensor technologies with the next section. Section III starts describing the most important competences in perception, to proceed with a state of the art of perception algorithms and techniques grouped by competences. Sensors used on each work are enumerated, and their advantages and disadvantages discussed. Section IV gives a perspective of the evolution of perception in Automated Driving, presenting the most relevant works and demos in the history of the discipline with a focus in sensor technologies used for each one. Finally, section V contains a discussion of the current state of the discipline and the future challenges for sensors and perception in Automated Driving systems. It includes a review of the most relevant alliances between OEMs (Original Equipment Manufacturers) and technological companies involved in automated driving projects at the time of writing the article.

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II. Sensors and technologies

This work is focused in exteroceptive sensors, leaving proprioceptive sensors and communications out of the scope of the review. Exteroception in Automated Driving is related with information in the surroundings of the vehicle, as opposed to propioception that is related with the state of the vehicle itself (speed, accelerations, component integrity). Propriceptive sensors and communications are out of the scope of this review.

Next subsections present the advantages, drawbacks and current challenges for the three principal sensor technologies for exteroceptive perception in Automated Driving: artificial vision, radar and LiDAR. Each one is followed with a review of relevant emergent technologies in the field.

In II-D a taxonomy of information domains is presented. It is useful for several purposes. First it allows to link sensors technologies with perception algorithms described in section III, since the first provide the raw data needed by the second. Second, the categorization is used to structure the subsequent analysis (section II-E) about the suitability and adequacy of the presented sensing technologies for perception in Automated Driving. This last part includes also the expected performance under different environmental and weather conditions.

A. Artificial Vision

Artificial vision is a popular technology that has been used for decades in disciplines as mobile robotics, surveillance or industrial inspection. This technology offers interesting features, as the low cost of sensors –for most popular types– and providing range of information types including spatial (shape, size, distances), dynamic (motion of objects by analyzing their displacement between consecutive frames) and semantic (shape analysis).

Artificial vision technology face several challenges, especially in applications like automated driving:

- Varying light conditions: driving happens at day, at night, indoors, or at dusk or dawn with the sun close to the horizon. Dark spots, shadows, glares, reflections and other effects difficult the implementation of reliable artificial visible algorithms.
- Scenes with a High Dynamic Range (HDR) contain dark and strongly illuminated areas in the same frame, as entering or exiting a tunnel. Most sensor technologies have a limited capacity of capturing both extremes simultaneously, so that information is lost in one or the two sides (under- or overexposure).
- Low light and high speed: cameras need higher exposures time as illumination is weaker. Fast moving elements appear blurred, which can affect later processes as border or feature detection. Also, if the sensor does not capture light in its full surface simultaneously (rolling shutter) distortion effects can appear in those objects.

In [10] some of these problems are analyzed from the perspective of recording scenes in sports. In order to deal with these difficulties, different technologies and solutions have been proposed.

- High Dynamic Range imaging (HDR): common sensors in photographic and industrial cameras offer a dynamic range of 60-75 dB, while mixed illumination environments require at least 120 dB. An automotive grade sensor combining HDR capabilities and Near Infra-Red light detection is analyzed in [11]. In 2017 Sony launched a 120 dB automotive sensor and 2k resolution. In [12] a sensor with 130 dB range (global shutter) and up to 170 dB (rolling shutter) is presented for industrial safety application.
- Global shutter sensors and Rolling shutter compensation. In rolling shutter cameras the elements of the sensor capture light at different time intervals, causing moving objects to appear distorted and creating half-dark-half-light frames in scenes illuminated by flickering lights (LEDs, fluorescents). This effects can be corrected by a motion compensation software [13][14]. Global shutter cameras, on the other hand, have the ability to capture light in all the elements of the sensor simultaneously.
- Captured spectrum: Far infrared cameras (wavelength 900-1400 nm, also called thermal cameras) are effective for pedestrian and animal detection [15][16] in the dark and through dust and smoke. Near Infrared (750-900 nm) complements visible spectrum with a better contrast in high dynamic range scenes, and better night visibility. In [17] authors compare visible light, near infrared and far infrared cameras in different light and atmospheric conditions.

1) 3D technology: Traditional camera technology is essentially 2D, but there are some types of vision sensors that can perceive depth information. This section describes the three principal types that are already available as commercial devices, although not always targeting the automotive market.

Stereo vision: depth is calculated [18] from the apparent displacement of visual features in the images capture by two carefully calibrated monocular cameras pointing in the same direction and separated by some distance (known as baseline).

One of the greatest advantages of stereo vision systems is their capability to provide dense depth maps, as opposed to sparse sensors (e.g. LiDARs). Stereo vision drawbacks include issues with low-textured patterns (e.g. solid colors) that difficult establishing correspondences between frames.

Monocular SLAM (Simultaneous Location And Mapping) algorithms share some of the working principles of stereo system: the motion of a single monocular camera creates an artificial baseline between consecutive frames, from which depth and camera motion are estimated. Some works as [19][20] represent a good alternative to stereo sensors for location and mapping.

Structured light: a monocular camera coupled with a device that illuminates the scene with a known pattern of infrared light. The distortion of the light pattern when projected over an irregular surface is captured by the camera and translated to a depth map.

Structured light devices overcome some limitations of stereoscopic systems, they do not depend on texture patterns and lowering the computational burden. However, they require the same high-accuracy calibration [21] and its operative range (usually below 20 meters) is limited by the power of the emitter and the intensity of ambient light. Reflections can affect its performance.

Time-of-flight: an active sensing technology [22], based in the same round-trip-time principle of LiDAR sensors (see II-C): an emitter composed of infrared LEDs floods the scene with modulated light that is captured by the sensor after being reflected by elements in the environment. The round-trip-time can be calculated for each pixel based on the phase shift of incoming light, which is then translated to a distance.

Using a non-directed source of light (as opposed to the low divergence laser emitter in LiDAR) has advantages as the ability to create dense depth maps and a high refresh rate exceeding 50 Hz. However, its operative range is short for automotive applications (10-20 meters) and has problems working under intense ambient light. Some research lines as indirect time-of-flight [23], pulsed light time-of-flight or avalanche photodiodes [24] could increase working range to 50-250 meters.

2) Emerging vision technologies: In event-based vision the elements of the sensor (pixels) are triggered asynchronously and independently when they detect a change on light intensity (an *event*). The sensor produce a stream of events that can be grouped in time windows for getting a frame-like image. Independence of sensor elements raises the dynamic range of the sensor to 120 dB, allowing high speed applications in low light conditions. [25] shows tracking at 1000 FPS under regular indoor lightning conditions, although the sensor works in sub-microsecond time scales. Events can be the input to visual odometry [26] and SLAM [27] applications, relieving the CPU of time consuming operations on raw images.

There is an active line of research [28] around sensors capturing light polarization, which perform consistently under adverse meteorological conditions and provide exotic types of information (e.g. materials, composition, water in the road).

B. Radar

Radar technology use high frequency electromagnetic waves to measure the distance to objects based on the *round-trip time* principle, which is the time it takes the wave to reach the object, bounce on it and travel back to the sensor.

Most modern automotive radars are based on the Frequency-Modulated Continuous Wave (FMCW) technology, and use digital beamforming [29] to control the direction of the emitted wave. FMCW consists on emitting a signal with a well known and stable frequency that is modulated with another continuous signal that varies its frequency up and down (typically using a triangular shape). Distance is determined using the frequency shift between the emitted and reflected signals. Radars also exploit Doppler effect to get a direct observation of the relative speed of the target with respect to the sensor.

One of the strongest arguments for including radar sensing in automated vehicles is its independence of light and weather conditions. It works in the dark, and detections are almost equally good with snow, rain, fog or dust [30]. Long range radars can see up to 250 m in very adverse conditions, where no other sensor works.

Radar sensors present some difficulties and drawbacks:

- Sensible to target reflectivity: processing radar data is a tricky task, due to the heterogeneous reflectivity of the different materials. Metals amplify radar signal, easing detection of vehicles but increasing the apparent size of small objects as discarded cans in the road, while other materials (e.g. wood) are virtually transparent. This can cause false positives (detect a non existing obstacle) and false negatives (not detecting an actual obstacle).
- Resolution and accuracy: radars are very accurate measuring distance and speed along the line that connects the sensor with a target. However, horizontal resolution depends on the characteristics of the emitted beam. Raw angular resolution in digital beamforming systems falls between 2 to 5 degrees [31], that can be improved to 0.1-1 degrees using advanced processing techniques [32]. With this angular resolution, it can be difficult to separate (detect as independent targets) a pedestrian from a nearby car at 30 m distance. At 100 m distance it can be impossible to separate vehicles in neighbor lanes, determine if a vehicle is in our same lane, and even if a detection is a vehicle or a bridge over the road.

1) Emerging radar technologies: One of the most active research area is related with high resolution radar imaging for automobiles. Apart from benefits in target tracking and object separation, a higher resolution can get richer semantic information and enable further applications as target classification and environment mapping. An example can be found in [30], where a 90GHz rotating radar in the roof of a car is used to map the environment, including vehicles, static objects and ground. The paper [33] demonstrates the feasibility of radars operating between 100 and 300 GHz, analyzing atmospheric absorption and reflectivity of materials usually found in driving scenarios.

One of the key technologies that can lead to high resolution radar imaging are meta-material based antennas [34], [35] for efficient synthetic aperture radars. Some manufacturers as Metawave [36] are starting to offer products oriented to automotive sector based on the technology.

C. LiDAR

LiDAR (Light Detection And Ranging) is an active ranging technology that calculates distance to objects by measuring round-trip time of a laser light pulse. Sensors for robotic and automotive applications use a low power near-infrared laser (900-1050 nm) that is invisible and eye-safe. Laser beams have a low divergence for reducing power decay with distance, allowing to measure distances up to 200 m under direct sunlight. Typically, a rotating mirror is used to change the direction of the laser pulse, reaching 360 horizontal coverage. Commercial solutions use an array of emitters to produce several vertical layers (between 4 and 128) that generate a point cloud representing the environment. LiDAR sensors feature an extraordinary accuracy measuring distances, averaging a few millimeters in most cases and degrading to 0.1-0.5 meters in the worst cases. This makes LiDAR a good choice for creating accurate digital maps.

However, they have several drawbacks to take into account:

- Low vertical resolution: in low cost models, which usually feature less than 16 layers, vertical resolution (separation between consecutive layers) falls down to 2 degrees. At 100 m distance, this is translated into a vertical distance of 1.7 m. High end models reduce this to 0.2-0.4 degrees, but at a much higher cost.
- Sparse measures (not dense): Commercial device Velodyne HDL64 has a 2 mrad divergence [37] (0.11 degrees) and a vertical resolution of 0.42 degrees. At 50 meters distance, the 0.3 degree gap between layers is equivalent to a blind strip 0.26 meters tall. In low end devices (Velodyne VLP16) this gap grows to 1.5 meters. Small targets can remain undetected, and structures based on wires and bars are virtually invisible.
- Poor detection of dark and specular objects. Black cars can appear as invisible to the LiDAR, since they combine a color that absorbs most radiation with a non-Lambertian material that does not scatter radiation back to receiver.
- Affected by dense rain, fog and dust. Infrared laser beams are affected by rain and fog because water droplets scatter the light [38], reducing the operative range of the device and producing false measures in the front of the cloud. The effect of dust has been explored in [39]. LiDAR performance in these scenarios is worse than radar, but still better than cameras and human eye.

1) Emerging LiDAR technologies: FMCW LiDAR [40] emits light continuously to measure objects speed based on Doppler effect. In the last years some research prototypes suitable for the automotive market start appearing [41]. Apart from improving target tracking capabilities, observation of speed can be useful to enhance activity recognition and behavior prediction, for example by detecting the different speeds of limbs and body in cyclists and pedestrians.

Solid state LiDAR is an umbrella term that includes several technologies, two of which are oscillating micro-mirrors and Optical Phased Array (OPA). The first technology combines one or many laser emitters that are directed with micro-mirrors that can rotate around two axes, so that the beam can be directed within a cone. Manufacturer LeddarTech commercializes devices based on this technology [42]. Optical phased arrays [43] is a technology similar to that used for EBF radars. that allows to control the direction of the beam with high accuracy and speed. Quanergy [44] is one of the few manufacturers commercializing devices based on this technology.

OPA technology has additional advantages over mechanical LiDAR: the scan pattern can be random in the entire FoV (Field of View), which is great for characterizing fast moving objects. It is possible to observe only a region of interest within the FoV. Also, it is possible to augment the point density within each frame for better resolution. The three features can be combined to do fast low resolution inspection of the full FoV, and then tracking with high resolution the objects of interest for enhanced shape recognition even at far distances.

TABLE I
INFORMATION TAXONOMY IN AUTOMATED DRIVING DOMAIN

Category	#	Information type
Ego-vehicle	1	Kinematic/dynamic (includes position)
	2	Proprioceptive (components health/status)
Occupants	3	Driver awareness/capacities
	4	* Driver intentions (mind model)
	5	Passenger status (needs, risk factors)
Environment	6	Spatial features: location, size, shape, fine features
	7	Identification: class, type, identity
	8	Semantic features: signs, road marks, regulation
	9	Contextual factors: weather, driving situation (e.g. jam, off-road, emergency)
External actors	10	Spatial features: location, size, shape, fine features
	11	Kinematic/dynamic: position, motion
	12	Identification: class, type, identity
	13	Semantic features: vehicle lights, pedestrian clothes, gestures
	14	* Situational engagement: collaborative/aware (adults, other vehicles) vs non-collaborative/unaware (animals, children)

D. Relevant information domains

The task of a perception system is to bridge the gap between sensors providing data and decision algorithms requiring information. A classical differentiation between both terms is the following: data is composed by raw, unorganized facts that need to be processed. Information is the name given to data that has been processed, organized, structured and presented in a proper context.

The following taxonomy (table I) is tightly related with the goals of perception stage (covered in section III). It allows to present conclusions about the suitability of each sensor technology for the different perception tasks in a clear and organized way.

Elements with an asterisk are derived information. This is, they that can be inferred from sensed data but not directly observed. It is mostly related with internal state of external entities, as the intentions of human beings and animals.

E. Using sensors for perception

Sensor selection and arrangement is one of the most important aspects in the design of a perception system for automated vehicles. It has a great impact in its cost, with some setups having several times the price of the rest of the vehicle. This epigraph summarizes two aspects of the uttermost importance: type of information acquired and impact of environmental factors. For an analysis of spatial coverage and range see [45].

The characteristics of a sensing technology determines its suitability for acquiring certain types of information, and restricts its range of operative conditions. Figure 1 relates the principal sensing technologies currently used in the automotive market and Automated Driving initiatives with relevant types of information identified in Table I. The adequacy of a sensor for acquiring a certain type of information (or equivalently, the expected quality of that type of information when captured by that sensing technology) is classified in three levels: Good (green shading, tick), Medium (yellow shading, letter M) and Bad (red shading, letter B).

Sensors and perception are expected to work uninterruptedly during vehicle operation. Weather and other environmental

Type of information		Visión (mono)	Visión (3D)	Radar	LiDAR 2D	LiDAR 3D
Spatial configuration (6, 10)	Location	B	M	✓	✓	✓
	Size	✓	✓	M	✓	✓
	Shape	✓	✓	B	M	✓
	Fine features	✓	✓		B	M
Kinematics (11)	Velocity, accelerations	B	M	✓	✓	✓
Identification (7, 12)		✓	✓	M	B	✓
Regulation/semantics (8, 13)	Traffic signs	✓	✓			B
	Road marks	✓	✓			M
	Gestures (humans)	✓	✓			M
	Clothes (humans)	✓	✓			
	Vehicle lights	✓	✓			
Context (9)	Weather	✓	✓			
	Driving situation	M	M			M

Fig. 1. Sensor adequacy for relevant types of information

factor can degrade sensor performance, but each technology is affected in a different way. Figure 2 summarizes the effect of common external factors in the performance of the analyzed sensing technologies, using the same notation as Figure 1.

Technology	Low light (dark)	Direct sunlight	Rain	Dust / Fog
Vision (mono, visible light)	B	✓	M	B
Vision (stereo, visible light)	B	✓	M	B
Vision (near IR)	✓	✓	M	M
Vision (far IR)	✓	✓	M	M
Vision (ToF)	✓	✓	M	M
Radar	✓	✓	✓	✓
LiDAR 2D	✓	✓	M	M
LiDAR 3D	✓	✓	M	M

Fig. 2. Sensor robustness under atmospheric and environmental factors

III. Problems and Applications

This section analyzes the state of the art in perception systems for Automated Driving. A set of behavioral competences is identified, followed by a systematic literature review that analyzes the solutions for each category, organized by sensor technology.

A. Behavioral competencies

Behavioral competencies in Automated Driving "refers to the ability of an automated vehicle to operate in the traffic conditions that it will regularly encounter" [46]. The NHTSA defined a set of 28 core competencies for normal driving [47], that have been augmented to a total of 47 by Waymo [48] in their internal tests. Table II selects a subset of those behavioral competencies and arranges them in categories that are used to structure the state of the art in perception algorithms in a purpose oriented approach. This set of competences represents the link between perception and decision (planning), as a counterpart to the information taxonomy presented in the previous section (Table I), which linked sensors and perception algorithms. Both tables can be combined to evaluate the suitability of sensor technologies for creating some set of Automated Driving capacities.

The next subsections describe the state of the art in perception techniques for the three identified categories of behavioral competencies.

B. Automatic Traffic Sign Detection and Recognition (TSDR)

Traffic signs are visual devices with a well defined aspect, that transmit a clear and precise piece of information about traffic regulation, warnings about factors affecting driving and other informative statements. The spatial and temporal scopes of applicability are also defined in the sign, either explicitly or implicitly. Acquiring information from road traffic signs involves two major tasks: Traffic Sign Detection (TSD) which consists on finding the location, orientation and size of traffic signs in natural scene images, and Traffic Sign Recognition (TDR) or classifying the detected traffic signs into types and categories in order to extract the information that they are providing to drivers.

Below are shown the most relevant solutions according to the type of sensor and the technology used.

1) Camera based solutions: Cameras are the most common sensor for TSDR. They can be used for TSR, TSD or both at the same time. As an example of TSR, [49] proposes a method based on the Polar-Fourier Grayscale Descriptor, and [50] a learning method based on a histogram intersection kernel. For TSD, [51] proposes a method based on a fast Convolutional Neural Network (CNN) inspired in the YOLOv2 network. This algorithm can detect the position of the traffic sign and classify it according to its shape. [52] detects stop and yield signs with a statistical template built using color information in different color spaces (YCbCR and ErEgEb). TSD techniques can also be applied to traffic light detection, as in [53], where a Bayesian inference framework to detect and map traffic lights is described. A different approach is proposed by [54] that uses a dual focal camera system composed of a wide angle camera and a telephoto camera which is moved by mirrors in order to get higher quality images of the traffic signs. Camera sensors can also perform TSD and TSR tasks as is shown in the following works where first the signals are detected attending to their color or shape, and then they are classified using machine learning techniques (CNN or SVM) [55], [56], [57]. In [58] a system composed by eight roof-mounted cameras which takes images every meter perform offline TDSR to create a database with more than 13,000 traffic signs annotations

2) LiDAR based solutions: LiDAR sensors have been used for TSD. Their 3D perception capabilities are usefult to determine the position of the sign and its shape, and can also use the intensity of reflected light to improve detection

TABLE II
BEHAVIORAL COMPETENCES AND RELATION WITH INFORMATION TAXONOMY (SEE TABLE I)

Competence	Information type	Behavior
Automatic Traffic Sign Detection and Recognition (TSDR)	8	Detect Speed Limit Changes, Speed Advisories, Traffic Signals and Stop/Yield Signs
	8	Detect Access Restrictions (One-Way, No Turn, Ramps, etc.)
	8	Detect Temporary Traffic Control Devices
	6, 8	Detect Passing and No Passing Zones
Perception of the environment	8	Detect Lines
	6, 8	Detect Detours
	6	Detect faded/missing roadway markings, signs and other temporary changes in traffic patterns
	9	Perception in unanticipated weather or lighting conditions outside vehicles capability (e.g. rainstorm)
Vehicles, pedestrians and other obstacles detection	10, 12, 13	Detect Non-Collision Safety Situations (e.g. vehicle doors ajar)
	10, 11, 12, 13	Detect Stopped Vehicles, Emergency Vehicles, Lead Vehicle, Motorcyclists, School Buses
	6(, 1)	Detect Static Obstacles in the Path of the Vehicle
	6, 8, 9, 10, 11, 12	Detect Pedestrians and Bicyclists at Intersections, Crosswalks and in Road (Not Walking Through Intersection or Crosswalk)
	10, 11, 12	Detect Animals
	10, 12, 13	Detect instructions from Work Zones and People Directing Traffic in Unplanned or Planned Events, Police/First Responder Controlling Traffic, Construction Zone Workers Controlling, Citizens Directing Traffic After a Crash (Overriding or Acting as Traffic Control Device)

accuracy based on the high reflectivity of traffic signs. [59] performs detection in three steps: first the point cloud is filtered by laser reflection intensity, then a clustering algorithm is used to detect potential candidates, followed by a filtering step based on the lateral position, elevation and geometry that extracts the signs. [60] goes one step further and makes a primary classification attending to the sign shape (rectangular, triangular and circular).

3) Sensors Fusion solutions: A system that combines LiDAR and Cameras can improve the sign detection and recognition as it has the advantages and the information of both sources. [61] trains a SVM with 10 variables: 9 of different color spaces provided by the camera (RGB, HSV, CIEL*a*b*) and the intensity provided by the LiDAR. After 3D geometric feature verification of the detected signs, the classification is made using HOG features and a linear SVM. [62] method, first detects traffic signs from mobile LiDAR point clouds with regard to a prior knowledge of road width, pole height, reflectance, geometrical structure and traffic-sign size. Then traffic signs are normalized to perform classification based on a supervised GaussianBernoulli deep Boltzmann machine model.

C. Perception of the environment

The purpose of this competence is to characterize and describe the road, which represents the most direct piece of environment of a vehicle. This involves two different aspects: characterize road surface geometry and detect road marks (lanes and complements traffic signs as stops, turns or stopping lines).

Road marks, as traffic signs, are designed to be detected and correctly interpreted by human drivers under a wide variety of external conditions. This is achieved using reflective painting and high contrast colors. Cameras and less frequently LiDARs have been used for detecting them. Road geometry description has been approached using cameras, LiDARs and radars.

In the following lines, the most relevant works about this topic are presented, organized by the type of sensor they use.

1) Camera based solutions: can be grouped in three categories depending on the specific sensor configuration.

Single Monocular: It is the simplest configuration. Using only one camera looking at the road in front of the vehicle it is possible to estimate the road shape and its lanes, the position of the vehicle in the road and to detect road marks that provide driving information. A survey of the most relevant algorithms used for this purpose, mainly for camera sensors is presented in [63].

Multiple Monocular cameras: Some works [64], [65] arrange multiple cameras around the vehicle (typically four, one on each side) to get 360-degree visual information of the surroundings of the vehicle. A different configuration is used in [66], where two lateral cameras are used to localize the vehicle.

Binocular or Stereo: The main advantage of using binocular cameras is that, as they provide 3D information, it is possible to detect the ground plane and road boundaries [67], [68], improving road mark detection.

2) LiDAR based solutions: Main application of LiDARs in road perception is related with detecting the ground plane and road limits, as well as detecting obstacles that could occlude parts of the road. In recent works, LiDAR based solutions also take advantage of the higher reflectivity of road marks with respect to the pavement (gray and black material) to detect lane markings [69], [70] and pavement markings [71] Poor road maintenance can affect mark reflectivity to the point of making them undetectable by LiDAR. This can be solved by fusing LiDAR data with cameras able to perceive non reflective lane marks [64]. Some works use a 2D LiDAR sensor to extract road geometry and road marks [72], [73].

3) Radar based solutions: Radars have been used to determine road geometry based on the principle that the road acts as a mirror for the sensor, returning a very small amount of the emitted power, while the sides of the roads return a slightly higher amount of power. Road limits have been estimated using radar images, getting a maximum error of half a lane at zero distance from the host vehicle and less than one lane width at 50 meters distance. This information can be fused with camera images to improve both detections [74], [75], [76].

D. Vehicles, pedestrians and other obstacles detection

This section reviews the use of different sensors for detecting other elements in the road, including vehicles, pedestrians and any other kind of obstacle that may appear such as motorcycles, bicycles, animals, etc. The advantages and disadvantages of sensors for this application are discussed. This competence involves moving elements that can be in the path of the vehicle, so it requires extracting more information. Apart from detection and classification, it is also important to determine the position of obstacles with respect to the automated vehicle, their motion direction and speed, and future intentions when possible. This information will be the input to other systems like path planners or collision avoidance systems (reviewed in [77]).

1) Camera based solutions: The use of cameras for obstacle detection can be performed with different configurations as in the previous competences. Single monocular camera, multiple cameras, stereo cameras and infrared cameras are used in different works.

A camera can be placed on different locations. The front of the vehicle is the most common placement since the most critical obstacles will be in front of the vehicle, but many works explored other positions in order to increase the FoV. On the side-view mirror, in the passengers window [78] or looking backwards [79], it is possible to detect and track vehicles trying to overtake the ego-vehicle, helping to take the decision of lane-change [80], [81], [82]. An omnidirectional camera mounted on the top of the vehicle has been used in [83] to detect obstacles and estimate ego-motion. In addition to monocular cameras, stereo cameras are widely used for obstacle detection as they provide 3D information of the position of the obstacles. A large review of the different algorithms used for this kind of cameras can be found in [84]. Infrared cameras are independent of scene illumination and can obstacles at night [85]. Relevant moving elements (vehicles, pedestrians, animals) are easy to detect with this type of cameras because they are usually hot, but it have to be complemented with a different obstacle detection source (like in [86]), since cold obstacles like parked vehicles or trees can be not perceived. [87] presents and explains in detail several camera solutions and the algorithms used for detection.

2) LiDAR based solutions: LiDAR technology allows to detect and classify surrounding elements, providing a very accurate 3D position and its shape. As it is an active sensor its performance is not affected by the illumination of the scene, so it can work also at night. Several approaches for LiDAR obstacle detection are shown in [88].

3) Radar based solutions: The primary use of automotive radars is detection and tracking of other vehicles on the road. They provide information of target position and relative speed, which is very useful for collision avoidance systems and path planning algorithms. Radars have the advantage of a good performance in adverse weather conditions (night, rain, fog, etc), and a large range of detection over 150 m [89]. Because of its low resolution radar detections are usually fused with other sensors as cameras [90] or, in some works, with LiDAR [91].

4) Multiple sensors fusion solutions: This competence requires estimating a large number of variables simultaneously, creating difficulties for any single sensor solution. This is a good scenario for sensor fusion systems, that can combine the strengths of each sensor to improve the solution. Almost every possible combination have been tested, including radar and vision, LiDAR and vision, radar and LiDAR, and other multiple modalities. The most common ones are described in the following lines. Radar and LiDAR fusion [91] increases the precision of the speed obtained only with LiDAR and keeps a good position and speed estimation quality when radar is unavailable (especially in curvy roads). Radar and vision fusion techniques use radar information to locate areas of interest on the images, which are then processed to detect vehicles and improve their position estimation [92]. LiDAR and vision sensors are fused in [93]. Obstacles are detected and tracked with the LiDAR, and the targets are classified using a combination of camera and LiDAR detections.

IV. Relevant works and demos

This section describes some of the most relevant technological demonstrations, competitions, challenges and commercial platforms related with automated driving, starting from pioneering works in late 1980s until present day. Figure 3 shows the timeline, with the focus on the sensors equipped by each platform.

The timeline allows to discern different stages (”ages”) in the development of Automated Driving technology, and to identify trends and approaches from the perception point of view for Automated Vehicles.

A. Pioneer works (1980-2000)

Pioneer works in Automated Driving starts around mid-1980s. The Bundeswehr University of Munich developed automated vehicles based on visual guidance, as VaMoRs [94] (a large van) and VaMP [95] (a Mercedes 500 SEL). Perception was built over a saccadic vision system: cameras mounted on a rotating platform that allowed them to focus in relevant elements. Sixty transputers executed an intelligent 4-D approach to object tracking, delivering a huge amount of computational power according to the standards at that moment.

In early 1990s INRIA creates the concept of a ”Cybercar”, a small automated electric vehicle for shared urban use [96]. Project Praxitle [97] (a mixed public and industry initiative) led to a fully functional prototype. In 1997 the Cybercar debuts in Schippol airport to transport passengers, between the terminal and long stay parking [98]. The vision and LiDAR based vehicle lacked pedals and steering wheels and moved autonomously in a dedicated lane that included semaphores and some pedestrian crossings.

Also in 1997, the National Automated Highway System Consortium presented a demonstration of Automated Driving

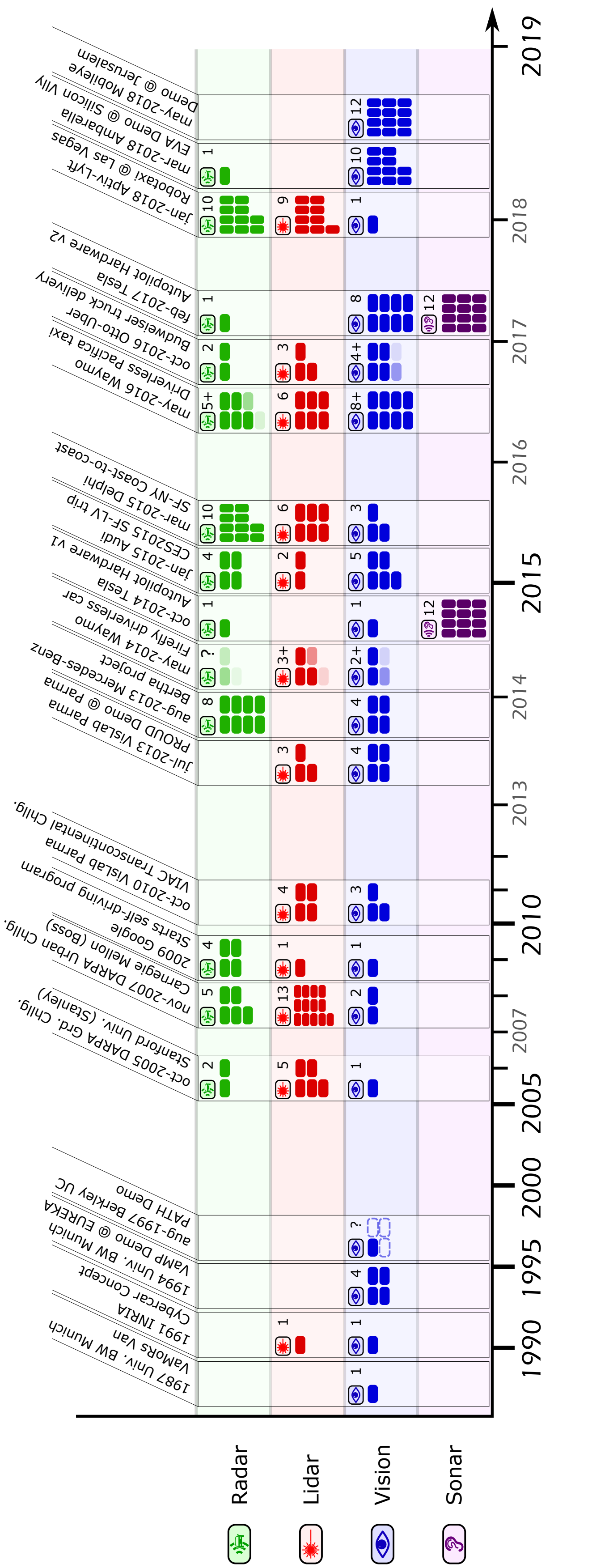

Fig. 3. Timeline of relevant AD demonstrators and its sensor setup for Perception systems

functionalities [99], intended to be a proof of technical feasibility. The demo showed road following functionality based on vision sensors, distance maintenance based on LiDAR, vehicle following based on Radar and other functionalities including cooperative maneuvers and mixed environments.

At that time, relevant functional demonstrators strongly relied on visual processing. The University of Parma started in 1996 a project with its vehicle ARGO [100], equipped with two cameras that allowed road following, platooning and obstacle avoidance. It completed over 2000 km of autonomous driving in public roads, and the full experience was compiled in a book [101].

B. Proof of feasibility (2000-2010)

In 2004, DARPA started its series of Grand Challenges to foster the development of robotics technology. The first edition ended without a declared winner, since no contestant manage to cover even a 10% of the 240km route including dirt roads and off-road sections. In 2005 edition, five of the 23 contestants finished the 212 km race. The winner was Stanford University racing team. Its vehicle Stanley carried 5 LiDAR units , a frontal camera, GPS sensors, an IMU, wheel odometry and two automotive radars [102]. These sensors were the input of a complex processing pipeline distributed over 6 computers, that involved perception and estimation techniques, artificial intelligence, 3D mapping, risk assessment and path planning.

For the next DARPA Challenge (Urban Challenge, 2007), participants had to complete a 96 km course in urban area, sharing the road with other participants and cars driven by professional drivers. Robots were required to obey traffic regulations, avoid obstacles and negotiate intersections properly. Carnegie Mellon University team won the contest with its vehicle Boss [103], featuring a complex perception system composed by two video cameras, 5 radars and 13 LiDAR (including a roof mounted unit of the novel Velodyne 64HDL). A cluster of 10 server blades processed a complex behavioral model [104] for covering all the expected situations.

These events triggered the attention of Google. The company hired around 15 scientists from the DARPA challenge, including the winners of 2005 and 2007 [105], [106]. Google's (and Waymo's) approach to self-driving vehicles is largely founded in LiDAR and 3D mapping technologies [107]. All their vehicles have had a roof-mounted spinning LiDAR: Toyota Prius (2009), the Firefly prototype (2014) and Chrisler Pacifica (2016-present).

Meanwhile, University of Parma created the spin-off VisLab in 2009. As opposed to Google approach, they represent one of the strongest supporters of artificial vision as the main component of perception systems for AD. In 2010 they completed the VisLab Intercontinental Autonomous Challenge (VIAC), where four automated vans drove from Italy to China [108]. The leading vehicle did perception (with cameras and LiDARs), decision and control, with some human intervention for selecting the route and managing critical situations [109]. The 13,000 km long trip included unmapped areas, degraded dirt roads and different traffic conditions. In 2013 the PROUD test put a vehicle with no driver behind the wheel in Parma roads for doing urban driving in real traffic [110].

C. Race to commercial products (2010-present)

In the last decade the landscape of Automated Driving has been dominated by private initiatives that foresee the coming of Level 4 and 5 systems in a few years. This vision gave birth to several companies devoted to this end, most of which were founded by people coming from the DARPA experience, or hired them to lead the project [107].

Examples include nuTonomy, (robotaxi company now acquired by Aptiv) co-founded by the leader of the MIT team in 2007 DARPA Urban Challenge. Cruise has been founded by a member of the same MIT team. Otto was founded by an engineer in Google's Street View project, they completed a beer delivery service with an automated truck in 2016. Uber hired up to 50 people from the CMU Robotics Lab for its self-driving car project. Zoox robotaxi company is co-founded by a member of the Stanford Autonomous Driving team with an expertise in LiDAR automated calibration [111], and Aurora company has a similar story with people from Uber, MIT and Waymo [112].

Car manufacturers reacted a bit slower. Some of them started independent research lines, for example BMW has been testing automation prototypes in roads since 2011 [113], but in the end most manufacturers have created coalitions with technological startups, as enumerated later in section V-B1.

Mercedes-Benz presented the Bertha project in 2013, based on an experimental S-Class 500 that drove a 103 km route in automated mode. Exteroceptive perception relied in close-to-market sensors (8 radars and 3 video cameras), presented new concepts as the *Lanelets* for road representation [114] and other innovative solutions [115] processed in a heterogeneous computing platform (FPGAs, embedded processors).

This approach to perception –avoiding LiDARs as expensive and far from mass production devices– has been supported by other companies. As an example, Mobileye started working in embedded computer vision devices in 1999, and by 2015 their technology was present in more than 25 car brands. Some years ago they started working in a vision-only approach to Automated Driving [116]. After testing in real conditions [117], they presented a demo with an automated Ford equipped just with 12 small monocular cameras for fully automated driving in 2018 [118].

Electric car manufacturer Tesla entered the automated driving scene in 2014. All their vehicles were equipped with a monocular camera (based on Mobileye system) and an automotive radar that gathered data and trained a "ghost" self-driving system based on reinforcement learning. In 2017 all manufactured Tesla vehicles have the hardware version 2, composed by a frontal radar, 12 ultrasonic rangers, and eight cameras that provide 360 degrees coverage. This sensor set together with nVidia Drive PX2 processing technology is claimed to be enough for full Level 5 automated driving [119], which will be available for a fee (when ready) through a software update.

In 2015 VisLab was acquired by Ambarella, a company focused in embedded video processing. They are working on low power chips able to process dense disparity maps from high resolution stereo cameras [120]. Its latest demo (Silicon Valley, 2018 [121]) fuse data from 10 stereo pairs (a total of 20 cameras) for creating a ultra-high resolution 3D scene delivering 900 million points per second. Long range vision relies in a forward facing 4k stereo pair together with a single automotive radar for better performance under low light or adverse weather conditions.

Delphi Automotive completed in 2015 an automated trip between San Francisco and New York city using a custom Audi Q5 with 10 radars, 6 LiDARs and 3 cameras onboard. Two years later they acquired nuTonomy, the first company to deliver a robotaxi service in public roads (available in reduced area of Singapore), and created Aptiv. Aptiv presented an automated taxi for CES conference in january 2018, as part of a 20 vehicle fleet that has been serving a set of routes in Las Vegas for some months. The taxis have an extensive set of 10 radars and 9 LiDARs embedded in the bodywork, plus one camera.

Meanwhile, Waymo had grown a fleet of Chrysler Pacifica minivans that has self-driven 10 million miles by october 2018. They put efforts on cutting prices and improving production scalability. For this purpose, they have created custom sensors: "two of the three LiDAR [...] are completely new categories of LiDAR" [122]. The long-range LiDAR is claimed to dynamically zoom into objects on the road, letting the vehicle see small objects up to 200 m away. This reminds the features of OPA solid state LiDARs (see section II-C1): random sampling across the scanning area and adaptive resolution. Although no details have been released to public, they claim to have reduced production cost of LiDAR sensors to less than one tenth in a few years.

V. Discussion

The last section of this article presents a discussion of the future challenges for sensors and perception systems in new automated vehicles, both from the technical and implantation point of view. A description of the next commercial initiatives and OEMs forecasts is shown followed by the final conclusions.

A. Future challenges

As shown in sections II and III there exist many works that solve the most important perception competences, based on different types of sensors and with a large variety of algorithms. However, there still exist some challenges that need to be solved in order to achieve a functional secure automated vehicle.

1) Technical challenges: Sensor setups in Automated Driving are usually focused on the areas relevant for the usual driving tasks: long range ahead from the vehicle, also long but no so much behind, and short-mid range in the laterals. This covers all the behavioral competences enumerated in section III. But plain 360 degree coverage can be insufficient for a commercial system expected to work in the real world. Some specific challenges like critical distances (too short and too large), occlusions or bad weather conditions do not have a proper solution yet.

Very short distance, including close to or below the car. A person, animal or object right below the vehicle or intersecting the path of the wheels represents a safety issue. While most situations can be anticipated when the element approaches the vehicle from the distance, it is not the case right before starting the vehicle, while executing high accuracy maneuvers in certain conditions (close to people or other moving elements).

This problem be tackled by adding redundant sensors in specific positions. Some commercial 360-degree-view parking systems [83] already seem to have a good visibility of vehicle immediate surroundings. Waymo claims to have a special LiDAR monitoring this area and even below the vehicle. In the future there will be a need of devices specific for this task that can make automated vehicles even safer than human drivers in such situations.

Very long distance Detection and classification above 200 meters is an open issue. Among current approaches, Ambarella integrates a Ultra High Resolution camera (cited in IV) that is claimed to be enough for discerning small objects at that target distance, subject to the limitations of visible light cameras.

Solutions based on saliency (a common term in artificial vision [123], [124], [125] to name relevancy or importance) can be an alternative to the high resolution and computational cost associated to brute force approaches. Solid state LiDAR capable of random and adaptive sampling is a potential candidate solution for such technology, achieving something similar to Waymo's claims about their custom built LiDARs.

Environmental and weather conditions Section II summarizes the suitability of common technologies under different conditions, some of which surpass human capacities. This is an always active field of research, because perception can solve what humans compensate with reasoning. Following the road when most marks are covered by snow, improving detection under heavy rain or dense fog are examples of problems that can be solved at sensing level without requiring further efforts on processing algorithms.

Intention detection Human drivers infer the intentions of pedestrians and vehicles combining subtle sensory hints with a mind model of the observed actor, and taking into account the context. Head pose, gaze direction, motion of limbs can be used to assess the awareness level and intentions of pedestrians and drivers.

Equivalently, some works can predict vehicle lane changes [126], risk at intersections [127] or pedestrian intentions [128], [129] applying machine learning and bayesian techniques to data acquired by exteroceptive sensors. Further sensor developments in resolution and accuracy potentially lead to much powerful intention predictors, that will result in safer and more fluent driving algorithms.

2) Implantation challenges: The final goal of research in automated driving is to bring technologies to market, either for private customers or for shared applications (automated fleets). Commercialization and implantation is feasible only if products fulfill certain scalability, costs, and durability requirements. Some sensors are among the most expensive and fragile components of a vehicle, so their implantation is a key factor in the development of automated driving vehicles.

Production scalability and costs. Mature technologies as visible light cameras and radars have already scaled up their production and reduced costs so that every vehicle can equip them without a significant impact on its price. This remains a challenge for LiDAR devices and other breakthrough technologies. The cost that is considered acceptable for a production vehicle, however, varies depending on the scenario. For private owned vehicles it must be kept at a rather small fraction of vehicle cost. Commercial fleet vehicles can afford higher prices because an Automated Driving system can compensate other costs (i.e. reducing the number of drivers). It is difficult to get an exact estimation, because Automated Driving can have a significant effect in mobility, economy an other factors. For a discussion on costs and impact of Automated Mobility services, see [130].

Durability and tolerance to failure. The perception system of an Automated Vehicle must work for long periods under harsh conditions, as the rest of critical components in a vehicle. In case of failure, redundancy and emergency fallback routines must be able to mitigate the problem and drive the vehicle to a safe state, but it is a threat that has to be avoided.

Mechanical LiDARs represent the clearest example of reliability issues: their mean-time-between-failures (MTF)(1,000 to 3,000 hours) is too low for automotive industry requirements (at least 13,000 hours) [131]. External factors can affect sensors. A stone chip can crack a glass while driving at high speeds ways, affecting the performance of video cameras and possibly LiDARs even when protected behind a plastic or glass layer. Another kind of external factors are intentional attacks [132]: radars can be jammed and a camera or a LiDAR can be blinded by the appropriate source of light. Future sensors will have to be robust against both types of external interference.

B. Commercial initiatives

In the last decade the automotive market has grown the offer and complexity of ADAS [133]. The most requested ADAS in 2009 [134] were Anti-lock braking system and Parking Assistance by Warning, which cannot be classified higher than SAE Level 0. Today most advanced cars today equip an ensemble of ADAS that place them somewhere between SAE Levels 2 and 3 in the scale of Automated Driving. Some examples are Tesla AutoPilot and Audi JamAssist, able to drive the vehicle under user supervision in specific scenarios.

1) OEMs in Automated Driving: Around 2015 most important OEMs decided to take serious initiatives towards bringing high and fully Automated Driving (SAE Levels 4 and 5) to the market. In order to accelerate their roadmaps, they established alliances with technological companies and startups.

It is difficult to get information about their research, further than public demonstrations and marketing products. However, these alliances with other companies, startups and technology/research centers are easier to trace and can hint about their approach to Automated Driving.

Table III shows a resume of the most important research and collaboration for Automated Driving with OEMs involved. The most relevant works are leaded by Ford, GM and Daimler, based on LiDARs, cameras and radar technologies. However, the influences of Waymo and Tesla, and the alliances with other actors (i.e.: NVIDIA, Apple or Intel-Mobileye-) plays an important role in this automated race. Another important

TABLE III
OEM PROJECTS AND ALLIANCES IN AUTOMATED DRIVING

OEM	Test site	Technologies	Since	Collaborations	Forecast	Test fleet
Ford	Detroit, Arizona & California (USA)	LiDAR, and mapping	∼2016	Argo, Velodyne, SAIPS, civilmaps.	Level 4 (2021)	Fusion Hybrid (∼100 by 2018)
GM	Detroit, S. Francisco & Scottsdale (USA)	LiDAR, HD map, radar, camera	∼2016	Waymo and Jaguar-Land Rover	2020 (Fortune)	∼50 vehicles (2017)
Renault-Nissan	Japan, USA & China	Front radar, LiDAR. Speed/steering control	∼2017	Transdev, Microsoft.	<2030 (Level 5) 2020 (Level 3)	—
Daimler	Germany	Vision, data fusion, radar.	2015	Bosch	2020	Commercial cars (Level 2)
Volkswagen-Audi Group	Germany	LiDAR, data fusion, adaptive cruise control, Trafic Jam Assist, self-parking	2015	Delphi (2015) Aurora (2017)	2025 (Level 4)	Commercial cars (Level 3, Traffic Jams)
BMW	Germany, China	Vision, LiDAR, DGPS	2011	Intel, Baidu, HERE	2022 (Level 5)	Commercial cars (Level 2)
Waymo	California (USA)	LiDAR, vision system, radar, data fusion, RT Path plan..	2010	Fiat-Chrysler, Velodyne.	—	100 autonomous Pacifica minivans
Volvo	Sweden. & Uber: San Francisco, Pittsburgh	Vision, LiDAR, GPS, V2I	2011	Uber (U.S), Autoliv (Sweden)	∼2020	Commercial cars (Level 2)
Tesla	USA	Camera, radar, AI	∼2015	Apple, Mobileye and Nvidia	∼2020 Level 5)	Commercial cars (Level 2)
Hyundai	South Korea	AI, LiDAR, Camera	2014	KIA, Aurora	AD Level 3. 2020 (Highways). 2030 (city streets)	—

consideration is that most the OEMs started their Automated program just two years ago. Other OEMs have also their focus in these technologies, but in this review only mention some of the most promising.

C. Conclusions

A survey about one of the most critical sensor parts in automated vehicles has been presented. Choosing the sensors configuration of an automated vehicle can be challenging. Each sensor has different strengths and weaknesses regarding the type of information acquired, overall accuracy and quality and working conditions. Usually the best solution consists in getting information from more than one type of sensor and fuse their information. It creates a more robust perception system as it has more data variety from different sources and also increases the safety as the fault of an specific sensor can be managed by another one. As all of these advantages, it also presents some challenges like finding a proper way to calibrate all those sensors, or making good decisions when two sensors have different outputs, or in other words, make a proper fusion of all the information. Computational power and energy consumption are also related with the sensors choice. The more data the vehicle gets, the more computational power it will be needed with it corresponding energy consumption. The challenge is: if the vehicle has more sensors, the final cost will increase and therefore it will be more difficult to produce those vehicles.

This survey has reviewed the most popular sensors technologies, describing their characteristics and how are they applied to get information useful to solve the main perception competences. It gives a global vision of different sensor configurations and techniques to obtain useful information from the environment.

The relevant works and demos provide a good perspective of how different manufacturers and research groups do perception tasks and which kind of sensors they use for that purpose. Finally, the section V-B1 can form an intuition about where are the manufacturers going in the autonomous vehicle process and how are they planning to get there.

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