A Review 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 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. Selection and arrangement of sensors represent a key factor in the design of the system. This survey reviews existing, novel and upcoming sensor technologies, applied to common perception tasks for ADAS and Automated Driving. They are put in context making a historical review of the most relevant demonstrations on Automated Driving, 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 future market trends in sensors technologies for Automated Vehicles.**

***Index Terms*—Automated Driving, LiDAR, Radar, Artificial Vision, Perception.**

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 aim to take the human driver out of the equation. This makes them a tool with the potential to reduce 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. This raises questions about its safety.

The architecture of Automated Vehicles is usually divided into three categories: perception of the environment, behavior planning and motion execution [3]. Automated 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.

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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 be the 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 Uber vehicle killed a woman that was crossing the road [6] in the night, dressed in dark clothes. Only the LiDAR provided a solid detection, that was discarded as a false positive by perception algorithms.

Sensor technologies have been surveyed previously in the literature, but usually centered on ADAS implementation [7], [8] or at a general level within Automated Driving [9]. One of the main contributions of this work is its focus on the relation between sensors and perception, which provide an integral view of the process that leads from raw sensor data to meaningful information for the driving task.

The content of the article is organized as follows. Section II reviews the sensor technologies commonly used for perception, its drawbacks and advantages, and related emerging technologies that can be used in the future. 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 are 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.

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).

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.

After that, 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 a subsequent analysis 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).

Cameras available in the market offer a wide range of configurations in resolution (from less than 0.25 to more than 40 Mpx), frame rate (up to thousands of frames per second (FPS)), sensor size, and optics parameters. However, Automated Driving poses some particular challenges to camera sensors and artificial vision technology:

Varying light and visibility 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 complicate the implementation of reliable artificial visible algorithms. Extending the capturing spectrum can solve some of these problems. Far infrared (FIR) cameras (wavelength 900-1400 nm) are effective for pedestrian and animal detection [10], [11], in the dark and through dust and smoke. Near Infrared (NIR)(750-900 nm) complements visible spectrum with a better contrast in high dynamic range scenes, and better night visibility. In [12] authors compare visible light, NIR and FIR cameras under different light and atmospheric conditions.

Scenes with a High Dynamic Range (HDR) contain dark and strongly illuminated areas in the same frame, as entering or exiting a tunnel. Common sensor technologies have single shot dynamic range of 60-75 dB, which cause a loss of information in the extremes (under- or overexposure). In 2017 Sony launched a 120 dB automotive sensor and 2k resolution. An automotive grade sensor combining HDR capabilities and NIR light detection is analyzed in [13] and the work [14] presents a sensor with 130/170 dB range (global/rolling shutter configurations).

A more extensive review of camera and sensor problems can be found in [15], from the perspective of recording scenes in sports.

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 [16] from the apparent displacement of visual features in the images captured 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 [17], [18] 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. Irregular surfaces produce an apparent distortion of the light pattern, that 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 textured surfaces and have a lower computational cost. However, they require the same high-accuracy calibration [19] 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. Is an active sensing technology [20] 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 [21], pulsed light time-of-flight or avalanche photodiodes [22] 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. [23] 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 [24] and SLAM [25] applications, relieving the CPU of time consuming operations on raw images.

There is an active line of research [26] 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 beam-forming [27] 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 [28]. 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 in part 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 beam-forming systems falls between 2 to 5 degrees [29], that can be improved to 0.1-1 degrees using advanced processing techniques [30]. 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 [28], 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 [31] demonstrates feasibility for 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 [32], [33] for efficient synthetic aperture radars. Some manufacturers as Metawave 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 NIR 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 degree horizontal coverage. Commercial solutions use an array of emitters to produce several vertical layers (between 4 and 128). This generates a 3D point cloud representing the environment. LiDAR sensors are a good choice for creating accurate digital maps, because of their high accuracy measuring distances which averages a few millimeters error in most cases and degrading to 0.1-0.5 meters in the worse. 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 [34] (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 weather conditions. NIR laser beams are affected by rain and fog because water droplets scatter the light [35], reducing its operative range and producing false measures in the front of the cloud. The effect of dust has been explored in [36]. LiDAR performance in these scenarios is worse than radar, but still better than cameras and human eye.

1) Emerging LiDAR technologies: FMCW LiDAR [37] 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 [38]. 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 directs laser beams using micro-mirrors that can rotate around two axes. Manufacturer LeddarTech commercializes devices based on this technology [39]. Optical phased arrays [40] 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 [41] is one of the few manufacturers commercializing devices based on this technology.

OPA technology can apply random-access scan patterns over the entire FoV (Field of View). This allows observing only specific regions of interest, and change beam density (resolution) dynamically. These features can be combined to do fast inspection of the full FoV with low resolution, and then tracking objects of interest with a higher resolution for enhanced shape recognition even at far distances.

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, while information is the name given to data that has been processed, organized, structured and presented in a proper context.

Table I presents a taxonomy tightly related with the goals of perception stage (section III). It allows to present conclusions about the suitability of sensor technologies for different perception tasks in a clear and organized way. Elements marked with an asterisk are derived information 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.

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

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 [42].

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

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

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)

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 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.

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" [43]. The NHTSA defined a set of 28 core competencies for normal driving [44], that have been augmented to a total of 47 by Waymo [45] 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, [46] proposes a method based on the Polar-Fourier Grayscale Descriptor, and [47] a learning method based on a histogram intersection kernel. For TSD, [48] 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. [49] 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 [50], where a Bayesian inference framework to detect and map traffic lights is described. A different approach is proposed by [51] 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) [52], [53], [54]. In [55] 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 useful to determine the position of the sign and its shape, and can also use the intensity of reflected light to improve detection accuracy based on the high reflectivity of traffic signs. [56] 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. [57] 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. [58] trains a SVM with 10 variables: 9 of different color spaces provided by the camera (RGB, HSV, CIEL*a*b*) plus reflection intensity observed by LiDAR. After verifying the 3D geometry of detected signs, a linear SVM classifier is applied to HOG features. [59] method detects traffic signs in LiDAR point clouds using prior knowledge of road width, pole height, and traffic sign reflectivity, geometry and size. Traffic sign images are normalized to perform classification based on a supervised Gaussian–Bernoulli 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).

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 under weather or lighting conditions outside vehicle's 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	Detect Static Obstacles in the Path of the Ego-Vehicle
	6, 8, 9, 10, 11, 12	Detect Pedestrians and Bicyclists at Intersections, Crosswalks and in the Road.
	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)

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. Using only one camera looking at the road in front of the vehicle it is possible to estimate its shape and lanes, the position of the vehicle in the road and detect road marks. A survey of the most relevant algorithms used for this purpose, mainly for camera sensors is presented in [60].

Multiple Monocular cameras. Some works [61], [62] arrange multiple cameras around the vehicle (typically four, one on each side) to get 360-degree visual coverage of the surroundings. A different configuration is used in [63], where two lateral cameras are used to localize the vehicle.

Binocular or Stereo. The main advantage of binocular cameras is their 3D perception capabilities. It makes possible to detect the ground plane and road boundaries [64], [65], 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 [66], 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 [67], [68] and pavement markers [69]. Poor road maintenance can affect marker 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 [61]. Some works use a 2D LiDAR sensor to extract road geometry and road marks [70], [71].

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 with 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 [72], [73], [74].

D. Detection of vehicles, pedestrians and other obstacles

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 vehicle, their motion direction, speed, and future intentions when possible. This information will be the input to other systems like path planners or collision avoidance systems (reviewed in [75]).

1) Camera based solutions: Different configurations have been used for camera based obstacle detection, including single monocular camera, multiple cameras, stereo cameras and infrared cameras.

Cameras can be placed in 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. A camera placed on the side-view mirror, in the passengers window [76] or looking backwards [77] can prevent backing crash and improve the decision of lane change maneuvers [78], [79], [80]. An omnidirectional camera mounted on the top of the vehicle has been used in [81] to detect obstacles and estimate ego-motion.

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 [82]. FIR cameras are independent of scene illumination and can spot obstacles at night [83]. Relevant moving elements (vehicles, pedestrians, animals) are usually hot and, thus, easy to detect with FIR cameras. However, this sensor has to be complemented with other technologies as in [84], since cold obstacles like parked vehicles or trees can be not perceived. [85] 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 [86].

3) Radar based solutions: The primary use of automotive radars is detection and tracking of other vehicles on the road, thanks to their high accuracy measuring target distances and relative speed, long range detection and performance in adverse weather conditions [87]. Radars have low angular resolution, causing misplacement of detected elements and reporting targets that are close to each other as a single larger object. A common solution consists on fusing radar detections with other sensors as cameras [88] or LiDARs [89].

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.

Radar and LiDAR fusion [89] 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 [90]. LiDAR and vision sensors are fused in [91]. 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 arranges them in a 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 focused in vision based techniques, which represented a huge computational burden for the embeddable computers of the time. Automated Vehicles VaMoRs [92] and VaMP [93] from Bundeswehr University of Munich used a saccadic vision system: cameras on a rotating platform that focus in relevant elements. The University of Parma started its project ARGO in 1996. The vehicle completed over 2000 km of autonomous driving in public roads [94], using a two camera system for road following, platooning and obstacle avoidance.

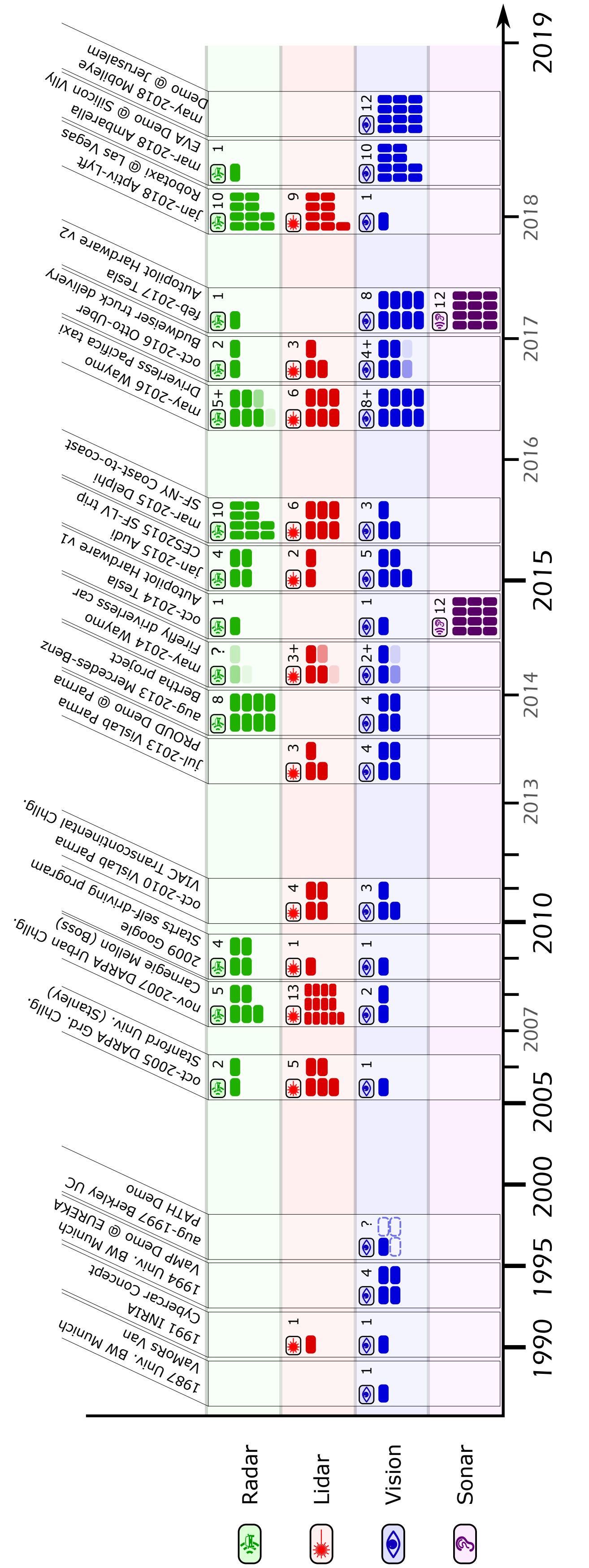

Fig. 3. Timeline: relevant AD demos and their exteroceptive sensor setup

The Cybercar concept is born in early 1990s [95] as an urban vehicle with no pedals or steering wheel. In 1997 a prototype is installed in Schippol airport to transport passengers between terminal and parking [96]. It used a LiDAR and vision system to drive automatically in a dedicated lane with semaphores and pedestrian crossings.

Also in 1997, the National Automated Highway System Consortium presented a demonstration of Automated Driving functionalities [97], 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.

B. Proof of feasibility (2000-2010)

In year 2004 DARPA started its Grand Challenge series to foster development of Automated Driving technologies. The achievements over those three years not only represented a huge leap forward, but also called the attention of powerful agents. Two first challenges (2004 and 2005) consisted in covering a route over dirt roads with off-road sections, with a strong focus in navigation and control. Stanford University won the 2005 edition, equipping its vehicle Stanley with 5 LiDAR units, a frontal camera, GPS sensors, an IMU, wheel odometry and two automotive radars [98]. The Urban Challenge (2007) changed the focus to interaction with other vehicles, pedestrians and obeying complex traffic regulations. Carnegie Mellon University team ended in first position with its vehicle Boss [99], [100], featuring a perception system composed by two video cameras, 5 radars and 13 LiDAR (including a roof mounted unit of the novel Velodyne 64HDL).

These events triggered the attention of Google. The company hired around 15 scientists from the DARPA challenge, including the winners of 2005 and 2007 [101], [102]. Google's (and Waymo's) approach to self-driving vehicles is largely founded in LiDAR and 3D mapping technologies [103]. All their vehicles have had a roof-mounted spinning LiDAR: Toyota Prius (2009), the Firefly prototype (2014) and Chrysler Pacifica (2016-present).

The University of Parma created the spin-off VisLab in 2009. They are strong supporters of artificial vision as the main component of perception systems for AD. In 2010 they completed the VisLab Intercontinental Autonomous Challenge (VIAC): four automated vans drove from Italy to China over public roads that included degraded dirt roads and unmapped areas [104]. The leading vehicle did perception (with cameras and LiDARs), decision and control, with some human intervention for selecting the route and managing critical situations [105]. In 2013 the PROUD test put a vehicle with no driver behind the wheel in Parma roads for doing urban driving in real traffic [106].

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 [103].

Examples include the nuTonomy (co-founded by the leader of the MIT team in 2007 Challenge), Cruise (founded by a member of the same team), Otto (founded by a participant in 2004 and 2005 Challenges), Uber (hired up to 50 people from the CMU Robotics Lab), Zoox robotaxi company (co-founded by a member of the Stanford Autonomous Driving team) [107], and Aurora (similar story with people from Uber, MIT and Waymo [108]).

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 [109] and Mercedes-Benz Bertha project [110] drove in 2013 a 103 km route in automated mode using close-to-market sensors (8 radars and 3 video cameras), but in the end most manufacturers have created coalitions with technological startups as enumerated in section V-B1.

Mobileye started working in a vision-only approach to Automated Driving a few years ago. After testing in real conditions [111], they presented a demo with an automated Ford equipped just with 12 small monocular cameras for fully Automated Driving in 2018 [112].

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 enabled the Level 2-3 AutoPilot functionality. Starting 2017 new Tesla vehicles include the “version 2” hardware, composed by a frontal radar, 12 sonars, and 8 cameras. This sensor set is claimed to be enough for full Level 5 Automated Driving [113], which will be available for a fee (when ready) through a software update.

In 2015 VisLab was acquired by Ambarella, a company working on low power chips able to process high resolution dense disparity maps from stereo cameras [114]. Its latest demo [115] fused data from 10 stereo pairs into a ultra-high resolution 3D scene delivering 900 million points per second. Long range vision mix a forward facing 4k stereo pair with a 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. In 2017 they acquired nuTonomy (the first company to deliver a robotaxi service in public roads) 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 has grown a fleet of Chrysler Pacifica minivans that has self-driven 10 million miles by october 2018. Their efforts have reportedly cut prices of LiDAR sensors to less than one tenth in a few years. They claim to have created two “new categories of LiDAR” [116] in the way, one for close range perception including below the car, and the other for long range. The long-range LiDAR can reportedly zoom dynamically 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.

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*

Sections II and III show many works that solve the most important perception competences, based on different types of sensors and with a large variety of algorithms. Translating these solutions into a functional, safe and secure commercial Automated Vehicle requires overcoming additional difficulties.

1) Technical challenges: Sensor setups in Automated Driving are usually focused on the areas relevant for the usual driving tasks (covered in section III). But for a commercial system expected to work in the real world there are still some specific challenges that 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 can be tackled by adding redundant sensors like [81] which uses a 360-degree-view parking system or a special LiDAR monitoring this area used by Waymo. In the future there will be a need of specific devices for this task.

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 [117], [118], [119] 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, 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.

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. It is difficult to get an exact estimation of an acceptable cost, it depends on the use of the vehicle (private or commercial fleet) in between many other factors. For a discussion on costs and impact of Automated Mobility services, see [120].

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. Low mean-time between-failures (as for mechanical LiDARs), external factors (a stone chip at high speeds can damage a sensor) or intentional attacks [121] are important factors to consider in the future sensors technologies.

B. *Commercial initiatives*

In the last decade the automotive market has grown the offer and complexity of ADAS [122]. The most requested ADAS in 2009 [123] were Anti-lock braking system and Parking Assistance by Warning (SAE Level 0). Today most advanced cars equip an ensemble of ADAS that place them between SAE Levels 2 and 3.

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 startups and technology/research centers that can hint about their approach to Automated Driving.

Table III shows a resume of the most promising research and collaboration for Automated Driving with OEMs involved. The most relevant works are leaded by Ford, GM and Daimler. However, the influences of Waymo and Tesla, and the alliances with other actors (NVIDIA, Apple or Intel-Mobileye) plays an important role in this automated race. Another important consideration is that most of the OEMs started their Automated program just two years ago.

C. *Conclusions*

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. This survey has reviewed the most popular sensors technologies, describing their characteristics and how they are applied to get useful information to solve the main perception competences. The

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)	—

relevant works and demos section 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 how manufacturers are approaching the development of Autonomous Vehicles and how are they planning to get there.

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