

Article

A Survey of Sensor Systems/Technologies for Perception in ADAS and Automated Driving

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Academic Editor: name

Version October 17, 2018 submitted to Sensors

Abstract: 20+ years of research on ADAS, Level 2-3 systems already commercially available. Automated Driving still in research phase, but with several companies working towards commercial platforms. These systems are based on the input provided by a set of sensors, which allow to describe the state of the vehicle, its environment and other actors. Innovation comes in two ways: new sensing technologies that overcome existing perception limitations and processing/fusion algorithms that transform raw data into more complete, accurate and meaningful information. This survey reviews existing and upcoming sensor solutions applied to ADAS/Automated Driving, based in both well known and novel sensing technologies. They are put in historical context reviewing the sensing setup of relevant demonstrators developed by academic and public institutions. Finally, the article presents a snapshot of current situation in commercial/industrial applications by identifying most relevant manufacturers and company alliances towards Automated Driving.

Keywords: keyword 1; keyword 2; keyword 3 (list three to ten pertinent keywords specific to the article, yet reasonably common within the subject discipline.)

1. Introduction

Every year more than one million people die on road accidents, and several million more get injured. In addition to the social cost, it also has an important economic impact for nations worldwide. According to [1], 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. This is likely to be extrapolable to the rest of the world. Automated Driving systems, also called self-driving vehicles, aim to take the human driver out of the equation. Thus, they are thought 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. Highly advanced ADAS, like Adaptive Cruise Control (ACC), Automatic Emergency Braking (AEB) or Lane Keep Assistant (LKA) are currently available at the market and highly accepted between users. Also, some recent demos like Waymo or Tesla (discussed in detail in Section 4) shows how future autonomous vehicles will be. However, there are still many research challenges, such as navigation in urban dynamic environments, accurate obstacle avoidance capabilities, environment understanding in real-time, and perception uncertainties among others. This research is needed to allow cooperative maneuvers between automated and semiautomated vehicles, which still need further efforts in real implementation, specifically in urban environment.

The architecture of autonomous vehicles is usually divided into three categories: Perception of the environment, behaviour planning and motion execution ??[Sagar Behere](sense-plan-act). The first category, perception of the environment, can be challenging for complex and dynamic environments. Autonomous vehicles obtain data of their surrounding making use of different sensors, such as cameras, LiDARS and radars. This raw data is then processed to extract relevant characteristics which are the input of the following categories (behaviour planning and motion execution), that will perform tasks such as path planning, collision avoidance or control of the vehicle among others ??[Bagloee2016].

This paper pays special attention to the sensor and perception stages. They especially important because they are the first link in the chain of Automated Driving, and a failure in that stage is propagated and has a chance of producing a severe accident. Some examples in the real world include the 2016 Tesla AutoPilot accident [2], where a man was killed after its car crashed a truck: the camera failed to detect the truck because it was painted in a color similar to the bright sky, while at the same time the radar detection was discarded as background noise by perception algorithms. Later in 2018, other Tesla vehicles have crashed against highway dividers after the lane following system failed to detect faded lines. Also in 2018, an experimental self-driving Uber vehicle killed a woman crossing the road [3] in the night, dressed in dark clothes. Only the LiDAR provided a positive detection, that was discarded as a false positive by perception algorithms.

Automated vehicles need to have a good understanding of the surrounding environment in order to drive safely in the roads. A state of the art of the different configurations and sensors used by different manufacturers, based on the most relevant demonstrators on Automated Driving, developed by research institutions and manufactures is presented. This topic has been widely investigated in the literature, but based usually on ADAS implementation. It is a key aspect in the future developments highly automated cars, where Real Time Motion planning needs more accurate and robust inputs. This paper makes an overview and analysis of the main problems, applications and sensor technologies available in the market.

The content of this paper is organized as follows. Section 2 describes the sensors commonly used for perception explaining the technologies that they use and the new emerging ones that will be used in the future. The most important competences in perception are discussed in section 3, describing the different sensors that can be used in each competence and discussing their advantages and disadvantages. Section 4 presents the most relevant works and demos, describing the kind of sensors used for each one. Finally, section 5 presents the most relevant alliances between OEMs and technological companies involved in automated driving projects, and contains a final discussion of the future challenges for sensors and perception in Automated Driving systems.

2. Sensors and technologies

En esta sección se discutirán las principales tecnologías de sensores (opcional: revisión de tecnologías emergentes).

Debemos cubrir el arco "sensores -> datos -> información", que lleva desde los sensores crudos hasta información relevante en AD. Esto nos permite enganchar con la sección Problems and applications.

2.1. 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 fields of study of ADAS and Automated Driving systems are large and heterogeneous. This makes necessary to use many types of information, that can be organized according to the following taxonomy / The following taxonomy gives an idea of the heterogeneity and complexity of ADAS/AD problems domain:

Table 1. Information taxonomy in Automated Driving domain

Category	#	Information type
Ego-vehicle	1	Kinematic/dynamic (includes position)
	2	Proprioceptive (components health/status)
Passengers/driver	3	Driver awareness/capacities
	4	* Driver intentions (mind model)
	5	Passenger status (needs, risk factors)
Environment	6	Spatial configuration: location, size, shape, fine features
	7	Identification: class, type, identity
	8	Regulation and semantics: traffic signs, road marks, other elements
	9	Contextual factors: weather, driving situation(e.g. jam, highway, off-road)
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 (adult pedestrians, other vehicles) vs non-collaborative/unaware (animals, children)

Elements with an asterisk are derived information. This is, something 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. These items also happen to belong to higher levels in the JDL model.

In this survey we are focused in perception of external elements, that is, the two last categories.

2.2. Principal sensor technologies for perception

There are a few categories of sensors that are included in almost every ADAS/AD system and are sufficient to cover any reasonable perception need. These categories are: artificial vision, radar, Lidar and ultrasonic.

Most of them are ranging sensors: the measured magnitude is distance to external objects, by means of the round-trip delay time of a electromagnetic wave (radar), a pulse of structured light (Lidar) or sound (ultrasonic). Artificial vision, in its most basic form, registers a grid of intensities and colors. This allows to extract additional information about the world, including traffic elements that are encoded visually to allow being interpreted by humans (signals, lanes, traffic lights).

Sensors provide raw data that sometimes can be used directly as useful information (e.g. GPS giving location/speed), or that must be processed/fused.

2.3. Artificial Vision

Artificial vision is a popular technology that has been used for decades in disciplines as mobile robotics, surveillance, industrial inspection. It acquires information about objects in the real world by analyzing their images as captured by photo and video cameras. Cameras are devices that gather light using a sensor composed by a grid of thousands or millions of individual detection elements. The amount of light captured by each element is translated more or less directly into the intensity of a pixel in the resulting image.

This technology offers interesting features, as the low cost of sensors –only some 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:

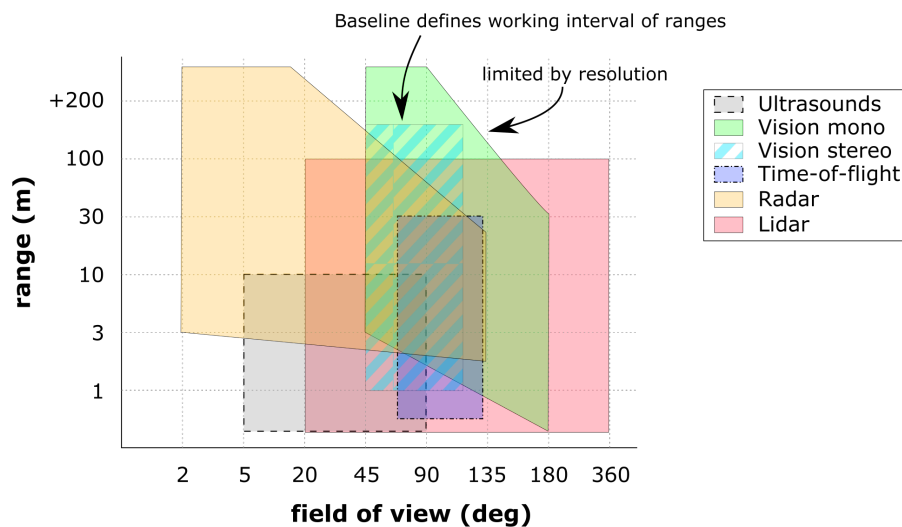


Figure 1. Range-FoV for depth sensors (3D sensing tecnology)

- Varying light conditions: driving is not limited to daylight conditions. It can also happen at night, indoors, or even worse, during dusk or dawn with the sun close to the horizon. Dark spots, shadows and other effects difficult the implementation of reliable artificial visible algorithms.
- High dynamic range in the scene (some areas are very dark and some others are strongly illuminated): while varying light conditions can be mitigated through dynamimc exposure mechanisms, HDR conditions are more difficult to deal with. Most sensor technologies have a limited capacity of capturing both extremes simultaneously, so that information is lost in one or the two sides. In automotive applications, this can mean detecting lane lines at the cost of not seeing preceding vehicles or viceversa.
- Objects moving at great 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)

In [4] 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.

- Rolling vs. Global shutter sensors. In rolling shutter cameras, either sensor technology (rows activated sequentially) or mechanical elements (a physical shutter moving to expose and occlude the sensor), the elements of the sensor capture light at differents time intervals. This have negative effects as: fast moving objects appearing distorted, or flickering lights (fluorescents, LEDs) creating images with some parts illuminated and others dark. Rolling shutter effects can be corrected by compensating scene motion vector, as proposed in [5][6]. Global shutter cameras, on the other hand, have the ability to capture light in all the elements of the sensor simultaneously.
- High Dynamic Range imaging (HDR): common sensors in photographic and industrial cameras offer a dynamic range of 60-75 dB (10 to 12.5 EVs), that is not sufficient in mixed illumination environments as entering or exiting tunnels. Sony launched its IMX390 automotive sensor with an extended 120 dB range (equivalent to 20 EVs) and 2k resolution. An automotive grade sensor combining HDR capabilities and Near Infra-Red light detection is analyzed in [7]. In [8] a sensor with 130 dB range (global shutter) and up to 170 dB (rolling shutter) is presented for industrial safety application.
- Captured spectrum: apart from visible light cameras, either in color or grayscale, automotive applications have used infrared sensors. Far infrared cameras (wavelength 900-1400 nm), also

known as thermal cameras, detect the emissions of hot objects, including living beings. Thermal cameras are effective for pedestrian and animal detection [9][10] in the dark and through dust and smoke. FLIR manufactured a system that was integrated in BMW's NightVision system since 2009 cameras. Near Infrared (750-900 nm) complements visible spectrum with a better contrast in high dynamic range scenes, improves night visibility. In [11] authors compare visible light, near infrared and far infrared cameras in different luminic and atmospheric conditions.

Light polarization represents an additional source of information which is know to be used by animals able to perceive it (some ants, mantis-shrimp). There is an active line of research [12] around sensors able to capture this feature, since it can be useful in conditions adverse for traditional sensors.

2.3.1. 3D technology

Although traditional camera technology is essentially 2D, 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*: a biology-inspired setup composed by two monocular cameras pointing in the same direction and separated by some distance (known as baseline). An object close to the sensor is perceived as located in different positions within each camera frame, while far objects have the same location on the two images. Depth is, thus, not a direct product of sensing but computed from raw measures. Extracting correspondences between pairs of frames is not trivial and a computationally demanding task.

Typically built with visible-light sensors, they are limited by the same factors. Stereo vision has issues with low-textured patterns (e.g. solid colors) because it difficults establishing correspondences between frames. Also, a careful calibration is needed to make sure that disparities are correctly translated to depths.

Good algorithms can return a dense depth map, as opposed to sparse sensors as LiDARs. Maximum and minimum perceived depth are limited by camera field of view and resolution: disparities smaller than one pixel of far objects could be not detected, calculating large disparities of very close objects are computationally expensive.

At present time it is possible to find several of-the-shelf sensors for stereo vision, either in the automotive field (¿REFS?) or as generic application products.

- *Structured light*: a monocular camera coupled with a device that illuminates the scene with a known pattern of infrared light. The distortion of the luminic 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 as depending on texture patterns and having a high computational cost. However, they require the same high-accuracy calibration [?] and have some additional limitations. Being an active sensor (projects light), their operative range is limited by the power of the emitter and the intensity of ambient light. Reflections can affect its performance. Typical devices are effective below the 20 meters mark, making them unfeasible for most automotive applications.

Microsoft Kinect, originally conceived as a gadget for its Xbox gaming console and now a discontinued product, is very popular for robotic applications. Microsoft RealSense is a product a product that combines stereoscopic vision with structured light, and is specifically targeted for outdoor applications requiring a short-mid range as drone navigation [].

- *Time-of-flight*: citeHansard2013 is a technology somehow related to LiDAR. A set of infrared LEDs emmit light modulated according a known scheme. The sensor captures light and measures, for each pixel, the phase shift with respect to emmitted light. This is translated to round-trip-time which is equivalent to a distance. The difference with LiDARs is that here the light source is a

"bulb" that fills the entire scene, while in the former a laser emits directed pulse. This makes time-of-flight devices less effective for large distances and with intense ambient light.

The advantages of time-of-flight sensors include: dense depth map, high accuracy and high refresh rate (easily up to 50 Hz)

Commercial products specify ranges up to 40 meters, with typical operative distances under 20 meters.

As an alternative, it is possible to extract 3D information by using camera motion for good performant SLAM algorithms [13][14], but at the date there are not commercial sensors integrating that capacity.

2.3.2. Emerging vision technologies

The most promising technology is known as event-based vision. It is a bioinspired technology developed by Zurich University and the ETH Zurich. It approaches the problem of processing and tracking fast moving images in a completely different way: instead of capturing fixed frames at discrete times, the elements of the sensor are triggered asynchronously and independently when a change on the intensity is detected. Each activation is called an event, and can be seen as something similar to the output of a feature detection algorithm for artificial vision applications. Events can be grouped in time windows for getting a frame-like image, but this window can be dynamically adapted for attending different time scales. Sensor time resolution goes down to microseconds, and [15] shows integration windows of 1 ms (1000 fps) in regular indoor lightning conditions to be sufficient for high speed tracking, thanks also to the 120 dB dynamic range of the sensor. An additional advantage is that the output can be used in raw form for applications as visual odometry [16] and SLAM [17] relieving the CPU of time consuming operations on raw images. More recently, a steering wheel control for automated driving systems based on deep learning has been shown in [18].

2.4. Radar

Radar technology use high frequency electromagnetic waves to measure the distance to objects in the environment. There are two principal technologies: pulsed radar emits a short burst and measures distance using the round trip time. Most modern automotive radars use Frequency-Modulated Continuous Wave (FMCW) where a signal with a well known and stable frequency 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. Both technologies allow to measure target speed based on Doppler effect.

Starting in 2004, EU allocated a permanent 5 GHz wide band around 79 GHz [19]. Short distance applications as blind spot detection, parking assistance, jam assistance and pre-crash measures use the upper part (77-81 GHz), since it offers a better resolution. Long distance applications as ACC use a radar signal around 76-78 GHz. However, manufacturers are implementing multifrequency chips that can switch between different functions dynamically.

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 [20]. Long range radars can see up to 250 m in very adverse conditions, where no other sensor works.

However, radar processing can be tricky due to the 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 and other factors make radars kind of "shortsighted", which is equivalent to say they have a low resolution. Horizontal and vertical positioning error grows with distance, so that at 100 m is difficult to say if an obstacle is actually on the vehicle lane, or if it is a bridge over the road.

As Automated Driving technology advances, radars are expected to go from its current use of detecting targets and measuring its speed to providing richer semantic information. Recent research turns around using higher frequency bands to increase resolution. This results in better shape recognition and separation of close targets that current technology reports as a single object. These features open the door to radar imaging and creation of detailed 3D maps. An example can be found in [20], where a 90GHz rotating radar in the roof of a car is used to map the environment, including not only other vehicles and static objects but also the ground. In [21] explores the feasibility of radars operating between 100 and 300 GHz. They present a prototype working at 150 GHz and conclude that atmospheric absorption and reflectivity of materials usually found in driving scenarios make this technology feasible, with the benefit of a high resolution that may enable radar imaging.

2.4.1. Emerging radar technologies

One of the most active research area is related with high resolution radar imaging for automobiles. Apart from research in early stages previously referred, a number of technological companies and startups are working in commercial products. For example, Arbe Robotics (<http://www.arberobotics.com/>) is working in a model with 300 m range, a field of view of 100 degrees horizontal, 30 degrees vertical, and a resolution of 1 degree azimuth and 2 degrees elevation. This model is expected to generate a full 4D (3D position plus speed) image of the scene at 25-50 Hz, thanks to the embedded machine learning and SLAM algorithms.

One of the key technologies that could lead to this achievement are metamaterial based antennas [22,23] for efficient synthetic aperture radars. Some manufacturers as Metawave (<https://www.metawave.co/>) are starting to offer products oriented to automotive sector based on the technology.

In a different line, ground-penetrating radar is a technology used from a long time ago in diverse areas ranging from archeology to industrial applications. MIT Lincoln Laboratory created a device [24] that can be placed below a vehicle to get a reading describing the geological properties of the first few meters under the ground. This reading is not affected by snow, water, dust or any other element over the surface of the road. The idea is to create maps that can be used later to localize vehicles, with an accuracy of a few centimeters. [?] Recently, Wavesense company (<https://wavesense.io/>) announced tests in snowy places and is close to commercialize this technology.

2.5. 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. Devices apt for robotic and automotive applications use a low power near-infrared laser (900-1050 nm) that is invisible, eye-safe and able to measure up to 200 m under direct sunlight. The long range is achieved thanks to laser beams having a low divergence, so that the reflected power does not decay too much with distance. LiDARs can be used for mapping environments. 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, combined with rotation, generate a point cloud that represents the 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 the favorite choice for creating accurate digital maps.

However, they have several drawbacks to take into account:

- Sparse measures (not dense): according to [25] typical lidar beam divergence is between 0.1 and 1 mrad. The commercial device Velodyne HDL64 covers a vertical FoV of 26.8 degrees using 64 layers (consecutive layers are separated 0.42 degrees), and has a 2.0 mrad divergence [26] (0.11 degrees). Horizontal resolution varies between 0.1 to 0.4 degrees. In most cases, then, there is

a high fraction of the total volume not illuminated by laser beams. Small targets or structures based on threads and bars can remain undetected.

- 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 gap to 0.2-0.4 degrees, but at a much higher cost.
- 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.
- High cost. High-end models have a cost between 25 and 75 k\$. Just a year ago, Velodyne models started at 9000 US\$ for the basic 16 layer device, although they have cut prices down to a 50% to face the recently appeared competitors. Now, some companies are selling equivalent models for less than 4000 US\$. Solid state lidars promise prices an order of magnitude smaller.
- Affected by dense rain, fog and dust. Infrared laser beams are affected by rain and fog because water droplets scatter the light [27], 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 [28]. Lidar performance in these scenarios is worse than radar, but still better than cameras and human eye.

2.5.1. Emerging LiDAR technologies

Direct speed measurement is a really nice feature for any sensor. Up to date, only radars were able to capture speed, for instance using FMCW signals. The same concept has been researched along last decades [29] applied to LiDARs that emit light continuously to measure objects speed based on Doppler effect. In the last years some research prototypes suitable for the automotive market start appearing [30], until recently a company named Blackmore announced a commercial version. Observation of speed can improve later perception stages. A direct use is to improve tracking of moving objects, but it makes possible to detect cyclists and discern when pedestrians are walking thanks to the different speeds of body and limbs.

Regarding LiDARs, however, the most popular emerging technology in the last years has been Solid State LiDAR. It offers advantages when it comes to operating under strong vibrations and dynamics, apart from being potentially smaller, cheaper and faster. However, the market does not offer products combining high resolution and a wide field of view, so mechanical devices are the only option for full 360-degree coverage and environment mapping.

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 [31]. Optical phased arrays [32] is a technology similar to that used for radars. An array of optical emitters generate coherent signals with a well controlled phase difference. This generates a far-field radiation pattern pointing in a direction that depends on the phase. This allows to control the direction of the beam with high accuracy and speed. Quanergy [33] is one of the few manufacturers commercializing devices based on this technology with a focus on the automotive sector, its S3 model features a 120 degrees FoV with a range of 150 m. They report a spot size of 5 cm at 100 m, that is comparable to a beam divergence of 0.5 mrad –4 times smaller than Velodyne HDL64 model.

OPA technology has additional advantages over mechanical lidars: the scan pattern can be random in the entire FoV, 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. This is similar to Waymo's claims about the LiDARs they have developed for their self-driving vehicles, as described in section 4.

2.6. Using sensors for perception

The characteristics of a sensing technology determines its suitability for acquiring certain types of information, and restricts its range of operative conditions.

Figure 2 relates the principal sensing technologies currently used in the automotive market and Automated Driving initiatives.

		Visión monocular	Visión 3D	Radar	Lidar 2D	Lidar 3D	Ultrasonidos
Spatial configuration (6, 10)	Location	Red	Yellow	Green	Green	Green	Red
	Size	Green	Green	Yellow	Green	Green	White
	Shape	Green	Green	Red	Red	Green	White
	Fine features	Green	Green	White	Red	Yellow	White
Kinematics (11)	Velocity, accelerations	Red	Yellow	Green	Green	Green	Red
Identification (7, 12)		Green	Green	Yellow	Red	Green	White
Regulation/semantics (8, 13)	Traffic signs	Green	Green	White	White	Red	White
	Road marks	Green	Green	White	White	Red	White
	Gestures (humans)	Green	Green	White	White	Yellow	White
	Clothes (humans)	Green	Green	White	White	White	White
	Vehicle lights	Green	Green	White	White	White	White
Context (6, 10)	Weather	Green	Green	White	White	White	White
	Driving situation	Yellow	Yellow	White	White	Yellow	White
	...	White	White	White	White	White	White

Figure 2. Sensor adequacy for relevant types of information

3. Problems and applications

En esta sección hablaremos de qué problemas hay que resolver en conducción automatizada y cómo se categorizan (SAE Levels, behavioral competencies NHTSA / California PATH, <https://storage.googleapis.com/sdc-prod/v1/safety-report/waymo-safety-report-2017-10.pdf>).

Desarrollar el "arco argumental": problema -> descomposición en habilidades/partes -> información necesaria.

Problems of interest in ADAS at different automation levels. Source: [MobilEye slides](#)

<i>Sensing technology</i>	Low light	Sun light	Rain/fog	Dust
<i>Monocular vision. Visible light</i>	Red	Green	Yellow	Yellow
<i>Stereo vision. Visible light</i>	Red	Green	Yellow	Yellow
<i>Near-infrared camera</i>	Yellow	Yellow	Yellow	Yellow
<i>Far-infrared camera</i>	Green	Yellow	Yellow	Yellow
<i>Time-of-Flight camera</i>	Green	Yellow	Yellow	Yellow
<i>Short range radar</i>	Green	Green	Green	Green
<i>Long range radar</i>	Green	Green	Green	Green
<i>Lidar 3D</i>	Green	Green	Yellow	Yellow
<i>Ultrasonic ranging</i>	Green	Green	Red	Red

Figure 3. Sensor robustness under atmospheric and environmental factors

341 3.1. Behavioral competencies

Table 2. Behavioral competences

Competence	#	Behaviour
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 or missing roadway markings or signage and/or other temporary changes in traffic patterns
	9	Perception in unanticipated weather or lighting conditions outside of 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(, 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)

342 3.1.1. Automatic Traffic Sign Detection and Recognition (TSDR):

343 There are two main tasks for getting information from on road traffic signs: Traffic sign detection
344 (TSD) which consists on finding the location, orientation and size of traffic signs in natural scene
345 images, and Traffic Sign Recognition (TDR), classifying the detected traffic signs into their specific
346 sub-classes in order to extract the information that they are providing to drivers. It also has two different
347 applications: Real time detection and recognition, used in ADAS or autonomous driving, and an
348 automatic road traffic sign mapping system, used for generating a database of all the traffic signs of an
349 area. This last application doesn't need to work on real-time. The two main sensors used for these tasks
350 are monocular cameras in different configurations (a single one, multiple focals or multiple cameras),
351 and LiDAR sensors. Below are shown the most relevant solutions according to the type of sensor, and
352 the technology used.

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, [34] proposes a method based on the Polar-Fourier Greyscale Descriptor, which applies the information about silhouette and intensity of an object. [35] uses a learning method based on an histogram intersection kernel to quantize features, and look-up table approach to encode them. For TSD, [36] proposes a method based on a fast Convolutional Neural Network (CNN) inspired in the YOLOv2 network. With this algorithm it is possible to detect the position of the traffic sign and classify it into Mandatory (blue ones) Danger (Triangle) and Prohibitory (red circle). [37] 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 [38], where a Bayesian inference framework to detect and map traffic lights is described. A different approach is proposed by [39] that uses a dual focal camera system composed of a wide angle camera assisted with a telephoto camera which is moved by a mirrors system in order to get higher quality images of the traffic signs. Camera sensors can also perform both tasks, detection and recognition as is shown in the following works. [40] uses local binary pattern method for detecting speed signals and a neural network for the recognition of the numbers of the speed limit sign. [41] presents a fast detection method based on traffic sign proposal extraction and classification built upon a color probability model and a color HOG combined with a convolutional neural network to further classify the detected signs into their subclasses. [42] performs detection and recognition tasks using a RGB colour segmentation and shape matching followed by support vector machine (SVM) classifier. [43] works with an eight roof-mounted cameras configuration that takes images every meter and are processed offline combining 2D and 3D techniques to create an available database, with more than 13,000 traffic signs annotations.

LiDAR based solutions: LiDAR sensors are also used, mainly for TSD, as they provide 3D information, used to localize the position of the sign and its shape, and information about the reflectiveness of the surface, which helps detecting traffic signs as they usually are high reflective. [44] performs detection in three steps: first the pointcloud is filtered by intensity of the laser reflected, then a clustering is applied to detect possible candidates and after that, a further filter based on the lateral position, elevation and geometry is applied to extract the sign. [45] goes one step further and is able to also make a primary classification attending to the sign shape (rectangular triangular and circular).

Sensors Fusion solutions: A system that combines both sensors, LiDAR and Cameras can improve the sign detection and recognition as it has the advantages and the information of both sources. [46] trains a SVM with 10 variables: 9 of different color spaces provided by the camera (RGB, HSV, CIE L*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. [47] 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 finally perform classification based on a supervised Gaussian–Bernoulli deep Boltzmann machine model.

Summary of sensors and their use for TSDR:

- **LiDAR:** Filtering for intensity (traffic signal has high Reflectance), 3D position and shape. Clustering for sign candidates
- **Camera**
 - Monocular B/W:** Feature extraction.
 - Monocular Color:** Color information. Classification with different methods: SVM, CNN, ..., or both, detection and classification.
 - Multiple cameras:** Mapping signals in roads, 3d position.
 - Multiple focals:** Short focal for detection and long focal for higher quality sign image.
- **Fusion LiDAR and Camera:** Using LiDAR intensity and 3d position and shape information for detecting, and camera colour and shape information for recognising

3.1.2. Perception of the environment

The purpose of this competence is to understand the environment of the vehicle: the road. It is usually divided into 2 tasks. The first one is to detect and recognise the road marks that complements the traffic signs (Stop turn, stopping lines) and the lane marks that delimit those lanes. With this information a map can be generated using localization information provided by a high precision GNSS based sensor in that places all the detected marks in their corresponding global position. The second task is related to the localization of the vehicles in the road. It can be either on map generated by the first map, or in unknown roads. There exist two critical facts that need to be considered in this competence: As most of the perception algorithms, this one requires a very high reliability, which is hard to get. The information provided by this kind of algorithms can be used to center the vehicle in the lane (lane-level localization), so a bad detection can be dangerous. It also has to work in very different kinds of environments, not only due to the different lanes signals that could vary from one country to another, but for different weather conditions. Different light intensity (Sunny day, night, shadows), different visibility conditions (fog snow rain) and different reflectivity of the road (wet or dry asphalt). These conditions can make hard to detect correctly the road marks. In the following lines, the most relevant works about this topic are presented, organized by the type of sensor they use.

Camera based solutions: Road infrastructures are designed so that human drivers can see them, they are optimized to provide visual information in different weather conditions (reflective painting, high contrast colours, etc). As cameras are also able to obtain visual information, they are the most commonly used sensor to do this task. There are different configurations used in the literature, that can be classify into: 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 roadmarks that provide driving information. A survey of the most relevant algorithms used for this purpose, mainly for camera sensors is presented in [48]. Multiple Monocular cameras: Some works use the around view monitor (AVM) technology. This configuration uses multiple cameras placed around the vehicle (typically 4, one at each side of the vehicle) in order to get 360° visual information of the surroundings of the vehicle. [49,50]. A different configuration is used in [51], 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, the groundplane can be detected easily. With this onformation of the groundplane, the road boundaries and the roadmarks detection is improved. [52,53]

LiDAR based solutions: LiDARs main usage is to detect the ground plane of the road and the limits of the road, and detect obstacles that could occlude parts of the road. In recent works, LiDAR based solutions also takes advantage of the higher reflectivity of lane marks (they are painted with white high reflective paint) with respect to road (which is black) to detect them. LiDARs, as they are active sensors, are less perturbable by light conditions (they can work even at night) than cameras, but

the resolution and the contrast of these detections are lower. As some roads are not good maintained, this higher reflectivity is lost in some places, so LiDAR information is usually fused with cameras that are able to perceive non reflective but white lane marks as they have higher contrast. Some works use 2D LiDAR sensor to extract the road geometry and roadmarks. It is a cheaper sensor, but it provides less information as it only measure distances in one plane. [49,54,55] Meanwhile, 3D LiDAR gives a more dense pointcloud with more information, improving lane and roadmarks detection, but with a higher cost. A curve detector and pavement markings detector are presented here [56–59].

Radar based solutions: The main advantage of Radar sensors is their ability to work in all weather conditions (darkness, rain, fog, snow, etc). But due to the poor image contrast of these types of sensors, the only usefull information for that competence that can be extracted is the position of the obstacles (in order to know occlusions of the road) and the road itself. Road, as it is plain, acts as a mirror for a radar sensor, returning very little power of the emitted, the sides of the roads return a slightly higher amount of power, and obstacles return a high amount of power. So road limits can be estimated using radar images, getting a maximum error of half a lane at zero distance from the host vehicle and remains within a full lane width even at 50 meters distance from the host vehicle. This radar information the is fused with camera images in order to improve both detections [60–62]

3.1.3. Vehicles, pedestrians and other obstacles detection

In this section it is reviewed the use of different sensors for detecting other vehicles in the road, pedestrians, and other kind of obstacles that may appear such as motorcycles, bicycles, animals, etc. The advantages and disadvantages of the use of each kind of sensor are discussed. For this competence, it is important not only to perform a good detection and classification, but also to detect correctly the position of those obstacles with respect to the ego-vehicle, so as their speed and movement intencion if possible. This information will be the input of systems like the path planner or the collision avoidance system (reviewed in [63]).

Camera based solutions: The use of cameras for obstacle detection can be performed with different configurations as in the previus competences. Estereo cameras, a single monocular camera, multiple cameras and InfraRed cameras are used in different works. A camera can be placed on different locations. On the front of the vehicle is the most common placement since the most critical obstacles will be in front of the vehicle, however, there exist different works that explore other positions in order to increase the field ov view. On the side-view mirror, in the passengers window [66] or looking backwards [67], it is possible to detect and track vehicles trying to overtake the ego-vehicle, helping to take the decision of lane-change [64? ,65]. On the top of the vehicle, omnidirectional cameras can be used to detect obstacles and estimate the motion of the vehicle[68]. 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 thiskind of cameras can be found in [69] Infrared cameras have the advantage of being independent of the scene ilumination, being able to detect obstacles at night [70]. As the main obstacles to detect (moving vehicles and pedestrians) are hot (emit in the infrared espectrum), they can be detected with this type of cameras, but it have to be complemented with a different obstacle detection source (like in [71]) since cold obstacles like parked vehicles or trees wont be percibed. In [72] many the different camera solutions and the algorithms used for detection are explained largely.

LiDAR based solutions: Whith this sensor, a detection and classification of different surrounding vehicles and pedestrians can be performed, obtaining a precise 3D position of these obstacles and the shape. As it is an active sensor, it performance is not affected by the illumination of the scene, so it can work also at night. In [73] different approachs for LiDAR obstacle detection are shown

Radar based solutions: Radars can be used to detect and track vehicles of the road. They provide information about the position and the relative speed of those obstacles. This information is very usefull for collision avoidance systems and path planning algorithms. They have the advantage of a good performance in adverse weather conditions (night, rain, fog, etc), and a large range of detection

(up to 150 m)[74]. Due to the low resolution of the final output of radars, these sensors are fused with other ones, usually cameras[75] or, in some works, LiDARS[76].

Microphone based solutions: Microphones sensors can be used to detect approaching vehicles from the rear side, an array of multiple microphones placed in the surroundings of the vehicle can estimate even the direction of these approaching vehicles [77].

Multiple sensors fusion solutions: As in the other competences, fusion sensors information is a very common approach in many works. The use of an specific sensor has strengths and weaks, for example, cameras provide more information in order to do a better classification of the obstacle, LiDAR provides a very precise position of the obstacle in a large range of view and radar gives information of the obstacle's speed, making easier tracking them. There exists many different combinations, like radar and vision, LiDAR and vision, acoustic and vision, radar and LiDAR, and other multiple modalities. The most common ones are described in the following lines. Radar and LiDAR fusion, like in [76] increases the precision of the speed obtained only with LiDAR and also obtained a good position and speed estimation when radar is unavailable (especially in curvy roads). Radar and vision fusion techniques usually use radar information to locate areas of interest on the images, and those images to detect vehicles and improve their position estimation [78]. LiDAR and vision, some works like [79] uses LiDAR information for detection and tracking, and both camera and LiDAR for classification.

4. 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 4 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.

4.1. Pioneer works (1980-2000)

Pioneer works in Automated Driving start around mid-1980s. The Bundeswehr University of Munich developed automated vehicles based on visual guidance, as VaMoRs [80] (a large van) and VaMP [81] (a Mercedes 500 SEL). Professor Ernst Dickmanns' team developed a saccadic vision system based on cameras mounted on a rotating platform that allowed cameras to focus in the details considered important. These systems mark a milestone because of the huge amount of computational power needed to process the visual information, according to the standards at that moment. It was accomplished by integrating sixty transputers that executed an intelligent 4-D approach to object tracking.

In early 1990s INRIA creates the concept of a "Cybercar", a small automated electric vehicle for shared urban use [82]. In 1993 starts project Praxitèle [83] as a mixed public and industry initiative that in a few years lead to a fully functional prototype. In 1997 the Cybercar debuts in Schiphol airport to transport passengers, between the terminal and long stay parking [84]. The vision and LiDAR based vehicle lacked pedals or 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 functionalities[85]. 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. The demo was intended to be a proof of technical feasibility of such technologies, creating the foundations for further developments.

At that time, relevant functional demonstrators strongly relied on visual processing. The University of Parma started in 1996 a project with its vehicle ARGO [86], a Lancia Thema equipped

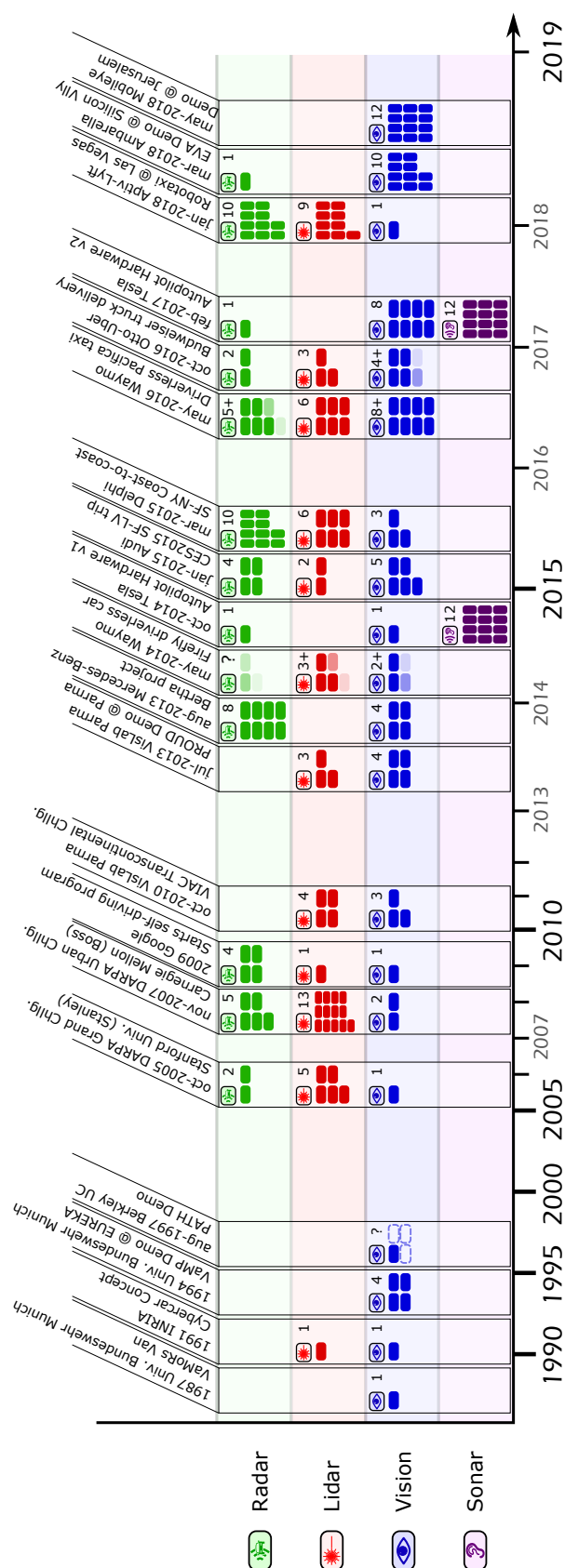


Figure 4. Timeline of relevant AD demonstrators and its sensor setup for Perception systems

with two cameras that allowed road following, platooning and obstacle avoidance. They detected lane lines and vehicles using classical image processing techniques including preprocessing steps, feature extraction, model fitting and spatio-temporal filtering. It completed over 2000 km of autonomous driving in public roads, and the full experience was compiled in a book [87].

4.2. *Proof of feasibility (2000-2010)*

However, it was not until 2004 that DARPA started its series of Grand Challenges to foster the development of robotics technology. The first edition consisted in travelling a 240 km long route comprising dirt roads and off-road sections. It ended without a declared winner, since no contestant managed to cover even a 10% of the route. The next year five of the 23 contestants finished the 212 km race of the DARPA Grand Challenge 2005. The winner was Stanley, the vehicle from Stanford University racing team. Stanley carried 5 LiDAR units used to create a 3D map of the environment with special attention to road geometry, a frontal camera, GPS sensors, an IMU, wheel odometry and two automotive radars [88]. These sensors were the input of a complex processing pipeline that involved perception and estimation techniques, artificial intelligence, 3D mapping, risk assessment and path planning, requiring 6 computers to do the processing.

The next DARPA Grand Challenge, known as Urban Challenge, took place in 2007. Participants had to complete a course of 96 km in urban area, while 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 [89], a modified Chevy Tahoe that included two video cameras, 5 radars and 13 LiDAR –including a roof mounted unit of the novel Velodyne 64HDL. Data was processed in a cluster of 10 server blades and featured a complex behavioral model [90] for covering all the expected situations.

These events had a huge scientific impact, but also triggered the attention of Google. The company hired around 15 scientists from the DARPA challenge, including the winners of 2005 and 2007 [92], [93]. Google vehicles have always relied in a roof-mounted spinning lidar as a cornerstone of their perception systems, starting with the original Toyota Prius (2009), the Firefly prototype (2014) and ending with Waymo's Chrysler Pacifica (2016-present). Google's approach to self-driving vehicles is largely founded in 3D mapping technologies [94], where LiDARs are the fundamental tool.

Meanwhile, University of Parma created the spin-off VisLab in 2009. They continued creating new pieces of technology and preparing outstanding Automated Driving demonstrators. 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 [95].

The leading vehicle did perception (with cameras and LiDARs), decision and control, with some human intervention for selecting the route and managing critical situations [96], and the rest of the vehicles followed it based on visual tracking and GPS points [96]. The 13,000 km long trip included unmapped areas, degraded dirt roads and different traffic conditions.

Three years later, the PROUD test put a vehicle with no driver behind the wheel in Parma roads for doing urban driving in real traffic [98]. It used a perception scheme similar to VIAC configuration, but more based in video and less in LiDARs.

4.3. *Race to commercial products (2010-present)*

In the last decade, the landscape of Automated Driving has been dominated by private initiatives. Automated vehicles between Levels 4 and 5 appear as a possibility in a few years, giving birth to several companies devoted to this end.

A significant number of them have been founded by people coming from the DARPA experience, or have hired them to lead the project [94]. An example is the robotaxi company nuTonomy (now acquired by Aptiv) was co-founded by the leader of the MIT team that ended #4 in 2007 DARPA Urban Challenge. Cruise has been founded by a member of the same MIT team in 2007. Otto, a company

that pursues self-driving truck –they completed a beer delivery service with an automated truck in 2016–, is founded an engineer in Google’s Street View project. Uber nuttered its self-driving car project with up to 50 people from the CMU Robotics Lab. Zoox robotaxi company is co-founded by a member of the Stanford Autonomous Driving team with an expertise in LiDAR automated calibration [99]. Aurora company has an similar history [100], with people from Uber, MIT and Waymo.

Car manufacturers have reacted a bit slower. Apart from collaborations with research entities, as Stanford-Audi Pikes Peak ascent in 2010 that was focused on control close to dynamic limits and did not any current perception [101], they have not really entered into scene until the last five years. Most of them have ended creating coalitions with technological startups, as enumerated later in section 5.2.1.

Mercedes-Benz presented the Bertha project in 2013, based on an experimental S-Class 500 that drove a 103 km route in automated mode. The vehicle was equipped exclusively with close-to-market sensors, and used 8 radars and 3 video cameras for exteroceptive perception. This work presented innovative solutions in the perception stage [102], with efficient algorithms processed in a heterogeneous computing platform (FPGAs, embedded processors) and new concepts as the *Lanelets* for road representation [103].

This approach to perception –avoiding LiDARs as expensive and far from mass production devices– has been supported by other companies. An interesting example is Mobileye, the Israel-based company started working in embedded computer vision devices in 1999, and by 2015 their technology was present in more than 25 car brands. Some years before they started working in a completely vision-based approach to perception in Automated Vehicles [104]. Their AI is claimed to hand the car with an "assertive driving" style that deals with traffic in a much less conservative way than its competitors, while being safe [106], [105]. After testing in real conditions [107], they presented a demo with an automated Ford equipped just with 12 small monocular cameras for fully automated driving in 2018 [108].

In 2014, the electric car manufacturer Tesla entered in the automated driving scene. All their vehicles were equipped with a monocular camera (based on the 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 version 2 hardware, composed by a frontal radar, the same 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, which will be available for a fee when ready –just a software update.

In 2015 VisLab was acquired by Ambarella, a company focused in embedded video processing. With their industrial support, they have achieved to manufacture low power chips able to process dense disparity maps from high resolution stereo cameras [109]. Its latest demo took place in Silicon Valley in 2018 [110], and does perception with 10 stereo pairs (a total of 20 cameras) for creating a ultra-high resolution 3D scene. The system delivers around 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. This is a different approach to visual-based perception, since stereo vision aims to get the best of both LiDARs and image processing in a single tool, with additional advantages.

The debate around price and production scalability for some sensors is still an open issue. Back to Waymo project, the Chrysler Pacifica equips custom sensors, "two of the three LiDAR [...] are completely new categories of LiDAR" [111]. 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 solid state LiDARs: 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 (which still can be high, since original 64-layer Velodyne costed over US\$ 75,000 when Waymo started its experiments).

Another important developer is Delphi. In 2015 they completed an automated trip between San Francisco and New York city using a custom Audi Q5 with 10 radars, 6 LiDARs and 3 cameras onboard. Sensors were integrated in the bodywork, giving the impression of being a regular vehicle. In 2017 Delphi 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 also embedded in the bodywork, plus one camera.

5. Discussion

To conclude the survey this section makes a discussion of the future challenges that new autonomous vehicles will need to cope with, technical and implantation ones. Then a description of the next commercial initiatives and OEMs in automation driving is shown followed by the final conclusions.

5.1. Future challenges

As shown in sections 2 and 3 there exist many works that solve the most important perception competences in different ways, using different types of sensors and with a large variety of algorithms. However, there still exist different challenges that need to be solved in order to achieve a functional secure autonomous vehicle.

5.1.1. Technical challenges

Plain 360 degree coverage is not enough

Sensor setups in Automated Driving are usually focused on the areas relevant for the usual driving task: long range ahead from the vehicle, also long but not so much behind, and short-mid range in the laterals. This covers all the behavioral competences enumerated in section 3, but there are some specific challenges like critical distances (too short and too large), occlusions, bad weather conditions and very fast events that are not usually covered and don't 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 is a problem that can be tackled by adding redundant sensors in specific positions. Some commercial 360-degree-view parking systems [68] already seem to have a good visibility of vehicle close 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 at 200 meters is an open issue. The resolution needed to monitor the whole area with the required accuracy is overwhelming. Among current approaches, Ambarella integrates a Ultra High Resolution camera (4k video, probably 8k) (cited in 4), that is claimed to be enough for discerning small objects at that target distance. The biggest problem is the raw computational power required to process so much information.

A different approach could consist on sensors able to determine saliency (a common term in artificial vision [112–114]), so that other adaptive sensors can focus on that area, increasing resolution, frame rate or accuracy. This reminds in some way the saccadic vision system used in Dickmann's pioneer vehicles [80,81], where a rotating platform was used to take images of areas of interest.

While the last part is something feasible today, for example using solid state LiDARs capable of random or adaptive sampling, the real challenge resides in the saliency part: design a sensor that can determine that something very far away can be relevant, without falling in the brute-force approach.

- *Indirect observations* (e.g. after occlusions) Humans are able to infer knowledge about the world based on subtle hints, e.g. see that someone is behind a car from a glimpse through vehicle glasses, or attending at the shadow projected in the road.

There are two different ways to approach this problem: the first one is to process the observations of high resolution sensors using and powerful processing algorithms. The second way is to create sensing technologies with super-human perception capabilities that can directly register such events or elements. Radars represent at present time the best example, since the propagation of electromagnetic waves has properties very different to usual biological sensing capabilities. For example, automotive radars can sometimes detect several vehicles in a row, totally occluded by the first one. Another example is WaveSense's ground-penetrating radar ?? previously presented in radar emerging technologies (section 2). The challenge remains open.

- Environmental and weather conditions Section 2 summarizes the suitability of common technologies under different conditions, some of which surpass human capacities. However, this is always an active field of research because perception can solve what humans compensate with reasoning. Following the road when most marks are covered by snow, or improving detection under heavy rain are examples of problems that can be solved at sensing level without requiring further efforts on processing algorithms.
- *Adaptation to very fast events ???*

5.1.2. Implantation challenges

The final purpose of research in autonomous driving is to create an autonomous vehicle that will be in the market (either for private customers or for commercial use in a fleet). This means that the final product have to fulfill certain scalability, costs, and durability characteristics so its production is feasible. The final cost has to be as low as possible, and the durability of the vehicle need to be similar to the current vehicle's. The sensors are one of the most expensive parts and one of the most fragile, so their correct implantation is a key factor in the development of autonomous 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. But it 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 vehicle, it must be kept at a rather small fraction of vehicle cost. In the case of fleet vehicles with a commercial use it can be higher because an Automated Driving system can compensate the cost of an employee. It is difficult to provide estimations, because Automated Driving can have a significant effect in mobility, economy and other factors. For a discussion on costs and impact of Automated Mobility services, see [115].

Durability and tolerance to failure

The perception system of an Automated Vehicle must work flawlessly for long periods under harsh conditions, as the rest of vehicle critical components. 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 have been around for about a decade, and are highly specialized devices mostly used with research purposes. The controversial CEO of Quanergy, Eldada, claims (<https://www.freightwaves.com/news/autonomous-trucking/quanergyceoripsvelodyne>) that mechanical LiDAR sensors are unsuitable for commercial automotive applications because the

mean-time-to-failure (MTF) "between 1,000 to 3,000 hours of operation" on the rotating components is far too low for industry requirements. Automakers want an MTF of at least 13,000 hours.

Solid state lidars based on vibrating micro-mirror (MEMS) can reduce costs and increase laser resolution but still have movable parts (micro-mirror), which makes them susceptible to vehicle vibrations and more fragile.

External factors can affect sensors. A stone chip can crack a glass while driving at high speeds ways, and this is something that can affect the performance of video cameras and possibly LiDARs even when protected behind a plastic or glass layer. It is desirable to create or improve sensing technology that can minimize the impact of that kind of events.

Another kind of external factors are intentional attacks. A radar 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 external interferences.

5.2. Commercial initiatives

At the end of the previous decade (2009), the most requested Advanced Driving Assistance Systems (ADAS) [116] were the Anti-lock braking system and the Parking Assistance by Warning. These systems cannot be classified higher than SAE Level 0.

In the last decade the automotive market have grown the offer and complexity of ADAS [117]. The 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.

The fact that manufacturers are starting to talk about SAE Levels is a sign that ADAS are completely integrated into the market and, thus, are not a subject of research per se anymore.

5.2.1. OEMs in Automated Driving

Back in 2010, most traditional vehicle manufacturers did not consider Automated Driving as a priority. In the last years, the achievements of technological pioneers (Google/Waymo, Uber, Tesla among others) gave place to early alliances between those companies that had the technology with OEMs that had the platform, the experience and the market.

By the end of 2018, all the important brands are involved in a race for creating the first highly automated vehicle (SAE Levels 4 and 5). It is difficult to get information about their research further than public demonstrations and marketing products. However, their alliances with other companies, startups and technology/research centers are easier to trace and can hint about their approach to Automated Driving.

Figure 5 gathers the most important coalitions for Automated Driving with OEMs involved.

5.3. Conclusions

Here it has been presented a survey about one of the most critical parts in autonomous vehicles, their sensors. Choosing the sensors configuration of an autonomous vehicle can be challenging. For all the perception competences, each sensor has different strengths and weakness. The task in which one sensor is not good, the other outperforms and vice versa. 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. That means that, if the vehicle has more sensors, the final cost will increase and therefore it will be more difficult to produce those vehicles.

OEMs	Test side	Technologies	Since	Collaborations	Forecast	Test fleet
Ford	Detroit, Arizona & California (U.S.A.)	AI, LiDAR, and mapping	~2016	Argo, Velodyne, SAIPS, civilmaps.	Level 4 (2021)	Fusion Hybrid sedans ~100 by 2018
GM	Detroit San Francisco & Scottsdale, Arizona (U.S.A.)	Lidar, very accurate map, radar, camera	~2016	Google's Waymo and Jaguar-Land Rover	before 2020 (Fortune)	Fifty vehicles have been built by GM (2017)
Renault-Nissan	Japan, EE.UU. & China	Maintains speed, Steering control, Front radar, Lidars	~2017	Transdev, Microsoft and TechCrunch (from Oath)	Fully autonomous car within the next 10 years. Level 3 -> 2020	---
Daimler	Germany	Vision, data fusion, radar.	2015 (Truck & F015)	Bosch	2020	Commercial cars (level 2)
Volkswagen Group (Audi)	Germany	Lidar, data fusion, adaptive cruise control, self-parking & TJA	2015	Audi -> Delphi (2015); Aurora (2017)	2025 (level 4)	Commercial cars (level 3 -> Traffic Jams)
BMW	Germany, China	Vision, lidar, DGPS	2011	Intel, and With Baidu & Nokia's HERE	Level 5 autonomous car on the road by 2022.	Commercial cars (level 2)
Waymo	California (U.S.A.)	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	U.S.A.	Camera, radar, AI	~2015	Apple, Mobileye and Nvidia	~Full automated 2020	Commercial cars (level 2)
Hyundai	South Korea	AI, LiDAR, Camera	2014	KIA, Aurora	AD Level 3-> Highways by 2020 and to city streets by 2030	---

Figure 5. OEM projects and alliances in Automated Driving

This survey has reviewed all the different sensors technologies available, 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 ??, which talks about commercial sensor systems for ADAS can form an intuition about where are the manufacturers going in the autonomous vehicle process and how are they planning to get there.

Supplementary Materials: The following are available online at www.mdpi.com/link, Figure S1: title, Table S1: title, Video S1: title.

Acknowledgments: All sources of funding of the study should be disclosed. Please clearly indicate grants that you have received in support of your research work. Clearly state if you received funds for covering the costs to publish in open access.

Author Contributions: For research articles with several authors, a short paragraph specifying their individual contributions must be provided. The following statements should be used “X.X. and Y.Y. conceived and designed the experiments; X.X. performed the experiments; X.X. and Y.Y. analyzed the data; W.W. contributed reagents/materials/analysis tools; Y.Y. wrote the paper.” Authorship must be limited to those who have contributed substantially to the work reported.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

MDPI	Multidisciplinary Digital Publishing Institute
DOAJ	Directory of open access journals
TLA	Three letter acronym
LD	linear dichroism

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