Article

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

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Abstract: After more than 20 years of research, ADAS and automated driving techniques are more common in new vehicles in the market and can be seen in public demonstrations and challenges. Fully Automated Driving is still in research phase, but with several companies working towards commercial platforms. These systems rely on the information provided by the sensors that they incorporate, which allow to describe the state of the vehicle, its environment and other actors. As sensors are the first stage of the automated driving architecture, they are a key factor in the developing phases. This survey reviews existing and upcoming sensor solutions applied to ADAS and Automated Driving, based in both well-known and novel sensing technologies, applied to the most common tasks in perception. They are put in context making an historical review of the most relevant works and demos developed by academic and public institutions and their sensing setup all over these technologies. Finally, the article presents a snapshot of the future challenges to be solved for sensors in perception and an overview of the commercial initiatives and manufacturers alliances that will show the intention of the market in sensors technologies for Automated Vehicles.

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 milion 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. Automated Driving systems, also called self-driving vehicles, aim to take the human driver out of the equation. Thus, they are designed to be a valuable tool towards reducing the number of traffic accidents.

Based on recent developments and demonstrations around the world, there is a tendency to think that Automated Driving with a high level of automation will be available in a few years. Advanced Driving Asistance Systems (ADAS), like Adaptative Cruise Control (ACC), Automatic Emergency Braking (AEB) or Lane Keep Asistant (LKA) are currently avalible at the market and highly accepted among users. Also, some recent demos like Waymo or Aptiv (discused 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.

Further 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 **??**. Autonomous vehicles obtain data of their sorrounding 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 stages (behaviour planning and motion execution), that will perform tasks such as path planning, collision avoidance or control of the vehicle among others.

Perception is a very challenging problem for several reasons. First, the environment is complex and highly dynamic, with some cases involving a large number of participants (dense traffic, populated cities). Second, it needs to work reliably under a wide range of external conditions, including lighting and weather (rain, fog, snow, dust). Perception errors are propagated and can be the cause of severe accidents. Some real examples 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 descarded 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.

This article reviews sensor technologies, perception algorithms and explores their relation, to provide an integral view of the process that leads from raw sensor data to meaningful information for the driving task. This topic has been previously investigated in the literature, but usually centered on ADAS implementation [4,5] or at a more general level within Automated Driving [6].

The content of the article is organized as follows. Section 2 describes the sensors commonly used for perception explaining the technologies, drawbacks and advantages, and related emerging technologies that can be used in the future. The section also defines a taxonomy of information that will allow to link sensor technologies with the next section. Section 3 starts describing the most important competences in perception, to proceed with a state of the art of perception algorithms and techniques grouped by competences. Sensors used on each work are enumerated, and their advantages and disadvantages discussed. Section 4 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 5 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 and technological companies involved in automated driving projects at the time of writing the article.

2. Sensors and technologies

This section presents a description of the principal sensing technologies for exteroceptive perception in Automated Driving. Advantages, drawbacks and challenges are described for each sensor, followed by some of the emergent technologies that can be relevant in the future of the discipline.

Sensors provide the raw data needed by perception algorithms, described in next section. In order to link both aspects, This section includes a categorization of information domains that will be referenced later in the article.

This section is concluded with two tables summarizing the adequacy of sensor technologies for acquiring the types of information identified, and expected performance under different environmental and weather conditions. [****this section*****]

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 following taxonomy is tightly related with the goals of perception stage (covered in section 3). It allows to present conclusions about the suitability of each sensor technology for the different perception tasks in a clear and organized way.

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, they that can be inferred from sensed data but not directly observed. It is mostly related with internal state of external entities, as the intentions of human beings and animals. These items also happen to belong to higher levels in the JDL model.[***ref a JDL?***]

This survey is focused in the perception of external elements, that corresponds to the two last categories (Environmenat and External actors).

2.2. Principal sensor technologies for perception

The common sensors that are present in most of the modern ADAS and autonomous vehicles projects 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).

This section is focused in the three principal technologies for Automated Driving: vision, radar and LiDAR.

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:

- 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 vicecersa.
- 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 [7] 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 oclude 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 [8][9]. 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 [10]. In [11] 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 [12][13] 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 [14] 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

[15] 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 esentially 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: depth is calculated [16] from the apparent displacement of visual features in the images capture by two monocular cameras pointing in the same direction and separated by some distance (known as baseline). In the last years, several good performant monocular SLAM algorithms [17][18] have been developed, which are not stereo systems but share some principles: they exploit the motion of a single monocular camera setup, creating an artificial baseline between consecutive frames that allow to estimate depths and camera motion at the same time.

One of the greatest advantages of stereo vision systems is their capability to provide dense depth maps, as opposed to sparse sensors as LiDARs. Their resolution, and maximum and minimum perceived depth are limited by camera field of view and imaging sensor resolution. Stereo vision drawbacks include issues with low-textured patterns (e.g. solid colors) that difficult establishing correspondences between frames. Also, it has a high computational complexity, and the pair of cameras requires a careful calibration to ensure proper translation of disparities to depths.

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 [19] and have some additional limitations as short operative ranges (usually below 20 meters), limited by the power of the emitter and the intensity of ambient light. Reflections can affect its performance.

Time-of-flight: is also an active sensing technology [20]. It is based in the same round-trip-time principle of LiDAR sensors: an emitter composed of infrared LEDs illuminates 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 laser emitter in LiDAR) has advantages and disadvantages. The advantages include the ability to create dense depth maps, its high accuracy and high refresh rate exceeding 50 Hz. The drawbacks include problems with intense ambient light and a short operative range (10 to 20 meters), making this technology unfeasible for many Automated Driving applications.

This can change in a short future. Alternative research line as indirect time-of-flight [21], pulsed light time-of-flight or avalanche photodiodes [22] appear to be close to commercialization. These technologies promise ranges between 50 and 250 meters.

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. Instead of capturing fixed frames at discrete times, the elements of the sensor (pixels) are triggered asynchronously and indepently when a change on the intensity is detected generating a stream of activations also called *events*. An event can be seen as something similar to the output of a feature detection algorithm for artificial vision applications. Events can be grouped in adaptable time windows for getting a frame-like image, reaching the microsecond scale for high speed tracking. The work [23] 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 [24] and SLAM [25] 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 [26].

2.4. Radar

Radar technology uses 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 (tipically 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 [27]. 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 dinamycally.

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.

However, radar processing can be tricky due to the reflectivity of the different materials: metals amplify radar signal, easening 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. 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 [28], 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 [29] explores the feasibility of radars operating between 100 and 300 GHz. They present a prototype working at 150 GHz and conclude that atmosferic 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 [30,31] 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 long time ago in diverse areas ranging from archeology to industrial applications. MIT Lincoln Laboratory created a device [32] 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. Tipically, a rotating mirror is used to change the direction of the laser pulse, reaching 360º 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 mesaures (not dense): according to [33] 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 [34] (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 iluminated 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 [35], 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 [36]. 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 usefull feature for any sensor. Up to date, only radars where able to capure speed, for instance using FMCW signals. The same concept has been researched along last decades [37] applied to LiDARs that emmit 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], 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 [39]. Optical phased arrays [40] 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 [41] 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

Sensor selection and arrangement is one of the most important aspects in the design of a perception system for automated vehicles. It also has a great impact in its cost, with some setups having several times the price of the rest of the vehicle. This epigraph summarizes some of the most important factors to consider: type of information acquired, physical coverage and impact of external factors in performance.

In first place, 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 1.

A perception system needs to cover adequately the relevant surroundings of the vehicle. Ideally, this includes 360 degrees around the vehicle up to several hundreds meters. Figure 2 shows usual operative range and field of view of relevant sensing technologies.

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 3 summarizes the effect of common external factors in the performance of the analyzed sensing technologies.

3. Problems and applications

This section analyze the state of the art in perception systems for Automated Driving. First of all a set of behavioral competences is identified, which serves as a link between perception and the next link in the Automated Driving chain. A systematic literature review is conducted to analyse the solutions for each category, organized by sensor technology.

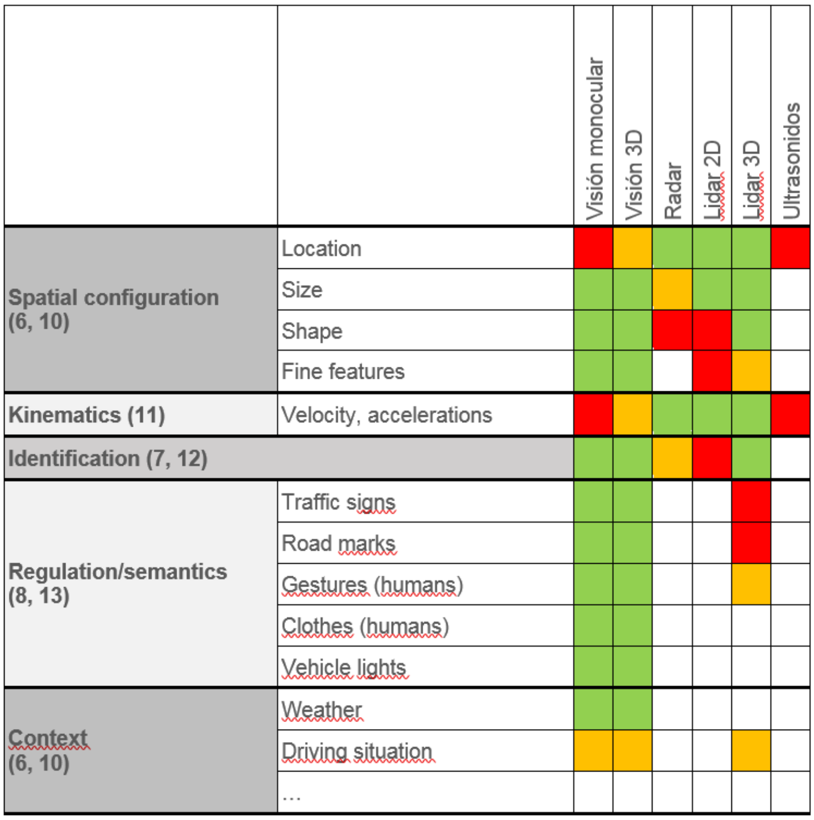

Figure 1. Sensor adequacy for relevant types of information

3.1. 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" [42]. The NHTSA defined a set of 28 core competencies for normal driving [43], that have been augmented to a total of 47 by Waymo [44] in their internal tests.

This section selects a subset of those behavioral competencies, interpreted from the point of view of perception requirements. Each competency will involve acquiring information that requires specific perception capacities. The selected competences are used to structure the state of the art in perception algorithms, in the next subsection, in a purpose oriented approach.

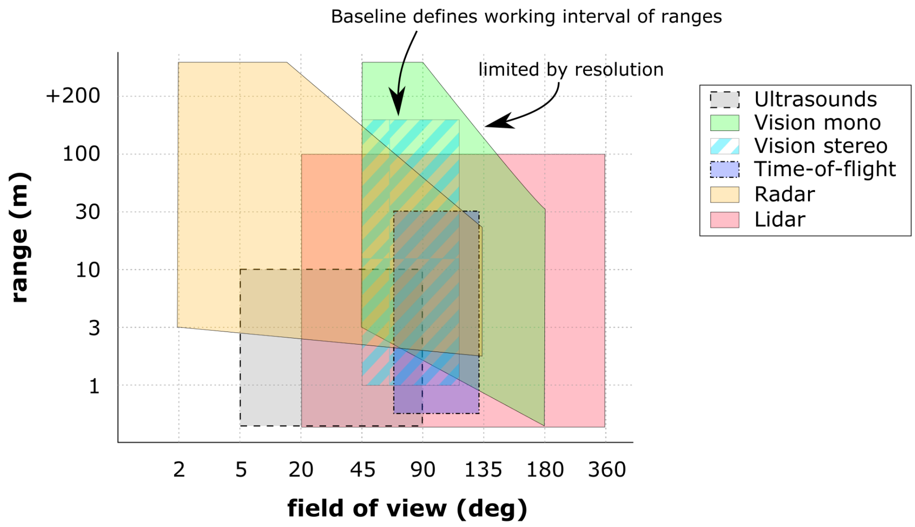

Figure 2. Range-FoV for depth sensors (3D sensing tecnology)

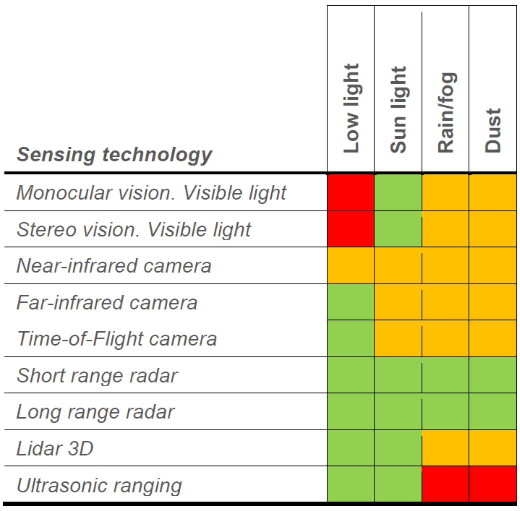

Figure 3. Sensor robustness under atmospheric and environmental factors

Table 2. Behavioral competences and relation with information taxonomy (see Table 1)

Competence	Information type	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 moadway 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

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 1), 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.

3.1.1. 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 road 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. Automatic TSDR has two different applications: Real time detection and recognition is used in ADAS or autonomous driving, and automatic road traffic sign mapping systems are used for generating a database of traffic signs of a certain area. This last application does not need to work on real-time.

Traffic signs are designed for human visual perception. Two sensors are mostly used for these tasks: monocular cameras in different configurations (single camera, multiple focals or multiple cameras) and LiDAR sensors. Below are shown the most relevant solutions according to the type of sensor and the technlogy 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, [45] proposes a method based on the Polar-Fourier Greyscale Descriptor, which applies the information about silhouette and intensity of an object. In [46] a learning method based on a histogram intersection kernel is used to quantize features, that are encoded in a look-up table. For TSD, [47] 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 into Mandatory (blue colored), Danger (triangle shaped) and Prohibitory (red circle). [48] 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 [49], where a Bayesian inference framework to detect and map traffic lights is described. A different approach is proposed by [50] 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 detection and recognition tasks as is shown in the following works. [51] uses local binary pattern method for detecting speed signals and a neural network for the recognition of the numbers of the sped limit sign. [52] presents a fast detection method based on traffic sign proposal extraction and classification built upon a color probability model and a color Histogram of Oriented Gradients (HOG) combined with a convolutional neural network to further classify the detected signs into subclasses. [53] performs detection and recognition tasks using a RGB colour segmentation and shape matching followed by support vector machine (SVM) classifier. [54] works with a system composed by eight roof-mounted cameras which takes images every meter. The dataset is processed offline combining 2D and 3D techniques to create a database with more than 13,000 traffic signs annotations.

LiDAR based solutions: LiDAR sensors have been used for TSD. Their 3D perception capabilities are usefult to determine the position of the sign and its shape, and can also use the intensity of reflected light to improve detection accuracy based on the high reflectivity of traffic signs. [55] 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. [56] goes one step further and makes a primary classification attending to the sign shape (rectangular, triangular and circular).

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. [57] trains a SVM with 10 variables: 9 of different color spaces provided by the camera (RGB, HSV, CIEL*a*b*) and the intensity provided by the LiDAR. After 3D geometric feature verification of the detected signs, the classification is made using HOG features and a linear SVM. [58] method, first detects traffic signs from mobile LiDAR point clouds with regard to a prior knowledge of road width, pole height, reflectance, geometrical structure and traffic-sign size. Then traffic signs are normalized to perform classification based on a supervised 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 compentence is to characterize and describe the road, which represents the most direct piece of environment of a vehicle. This involves two different aspects: characterize road surface geometry and detect road marks (lanes and complements traffic signs as stops, turns or stopping lines).

Road marks, as traffic signs, are designed to be detected and correctly interpreted by human drivers under a wide variety of external conditions. This is achieved using reflective painting and high contrast colours. 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, orginized by the type of sensor they use.

Camera based solutions: Camera based solutions have been grouped in three categories depending on the specific sensor configuration.

<u>Single Monocular</u>: 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 [59].

<u>Multiple Monocular cameras</u>: Some works [60,61] arrange multiple cameras around the vehicle (tipically 4, one on each side) to get 360-degree visual information of the surroundings of the vehicle. A different configuration is used in [62], where two lateral cameras are used to localize the vehicle.

<u>Binocular or Stereo</u>: The main advantage of using binocular cameras is that, as they provide 3D information, it is possible to detect the groundplane and road boundaries [63,64], improving roadmark detection.

LiDAR based solutions: Main application of LiDARs in road perception is related with detecting the ground plane and road limits, as well as detecting obstacles that could occlude parts of the road. In recent works, LiDAR based solutions also take advantage of the higher reflectivity of road marks with respect to the pavement (gray and black material) to detect lane markings [65,66] and pavement markings [67] However, poor road maintenance can severely affect mark reflectivity to the point of making them undetectable by LiDAR. This can be solved by fusing LiDAR data with cameras able to perceive non reflective lane marks [60]. Some works use 2D LiDAR sensor to extract road geometry and roadmarks [68,69].

Radar based solutions: Radars have been used to determine road geometry based on the principle that the road acts as a mirror for the sensor, returning a very small amount of the emitted power, while the sides of the roads return a slightly higher amount of power. Road limits have been estimated using radar images, getting a maximum error of half a lane at zero distance from the host vehicle and less than one lane width at 50 meters distance. This information can be fused with camera images to improve both detections [70–72].

3.1.3. Vehicles, pedestrians and other obstacles detection

This section reviews the use of different sensors for detecting other elements in the road, including vehicles, pedestrians and any other kind of obstacle that may appear such as motorcycles, bycicles, animals, etc. The advantages and disadvantages of sensors for this application are discused. 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 imortant to determine the position of obstacles with respect to the automated vehicle, their motion direction and speed, and future intentions when possible. This information will be the input to other systems like path planners or collision avoidance systems (reviewed in [73]).

Camera based solutions: The use of cameras for obstacle detection can be performed with different configurations as in the previuos competences. Single monocular camera, multiple cameras, stereo 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 [74] or looking backwards [75], it is possible to detect and track vehicles trying to overtake the ego-vehicle, helping to take the decision of lane-change [76**?** ,77]. An omnidirectional camera mounted on the top of the vehicle has been used in [78] to detect obstacles and estimate ego-motion. In adition to monocular cameras, stereo cameras are widely used for obstacle detection as they provide 3D information of the position of the obstacles. A large review of the different algorithms used for this kind of cameras can be found in [79]. Infrared cameras have the advantage of being independent of the scene ilumination, being able to detect obstacles at night [80]. Moste moving elements (vehicles, pedestrians, animals) are hot an emmit photons in the infrared espectrum, making them easy to detect with this type of cameras, but it have to be complemented with a different obstacle detection source (like in [81]), since cold obstacles like parked vehicles or trees can be not perceived. The article [82] presents and explains in detail many camera solutions and the algorithms used for detection.

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 [83].

Radar based solutions: The primary use of automotive radars is detection and tracking of other vehicles on the road. They provide information of target position and relative speed, which is very useful for collision avoidance systems and path planning algorithms. Radars have the advantage of a good performance in adverse weather conditions (night, rain, fog, etc), and a large range of detection over 150 m [84]. Because of its low resolution radar detections are usually fused with other sensors as cameras [85] or, in some works, with LiDARS [86].

Multiple sensors fusion solutions: This competence requires estimating a large number of variables simultaneously, creating difficulties for any single sensor solution. This is a good scenario for sensor fusion systems, that can combine the strengths of each sensor to improve the solution (). Almost every possible combination have been tested, including radar and vision, LiDAR and vision, radar and LiDAR, and other multiple modalities. The most common ones are described in the following lines. Radar and LiDAR fusion [86] increases the precision of the speed obtained only with LiDAR and keeps a good position and speed estimation quality when radar is unavalible (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 [87]. LiDAR and vision sensors are fused in [88]. Obstacles are detected and tracked with the LiDAR, and the targets are classified using a combination of camera and LiDAR detections.

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 starts around mid-1980s. The Bundeswehr University of Munich developed automated vehicles based on visual guidance, as VaMoRs [89] (a large van) and VaMP [90] (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 marked 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 [91]. Later, in 1993, the project Praxitèle [92] starts as a mixed public and industry initiative that in a few years lead to a fully functional prototype. In 1997 the Cybercar debuts in Schippol airport to transport passengers, between the terminal and long stay parking [93]. The vision and LiDAR based vehicle lacked pedals and steering wheels and moved autonomously in a dedicated lane that included semaphores and some pedestrian crossings.

Also in 1997, the National Automated Highway System Consortium presented a demonstration of Automated Driving functionalities [94]. 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 [95], a Lancia Thema equipped 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 [96].

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 manage 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 [97]. These sensors were the input of a complex processing pipeline that

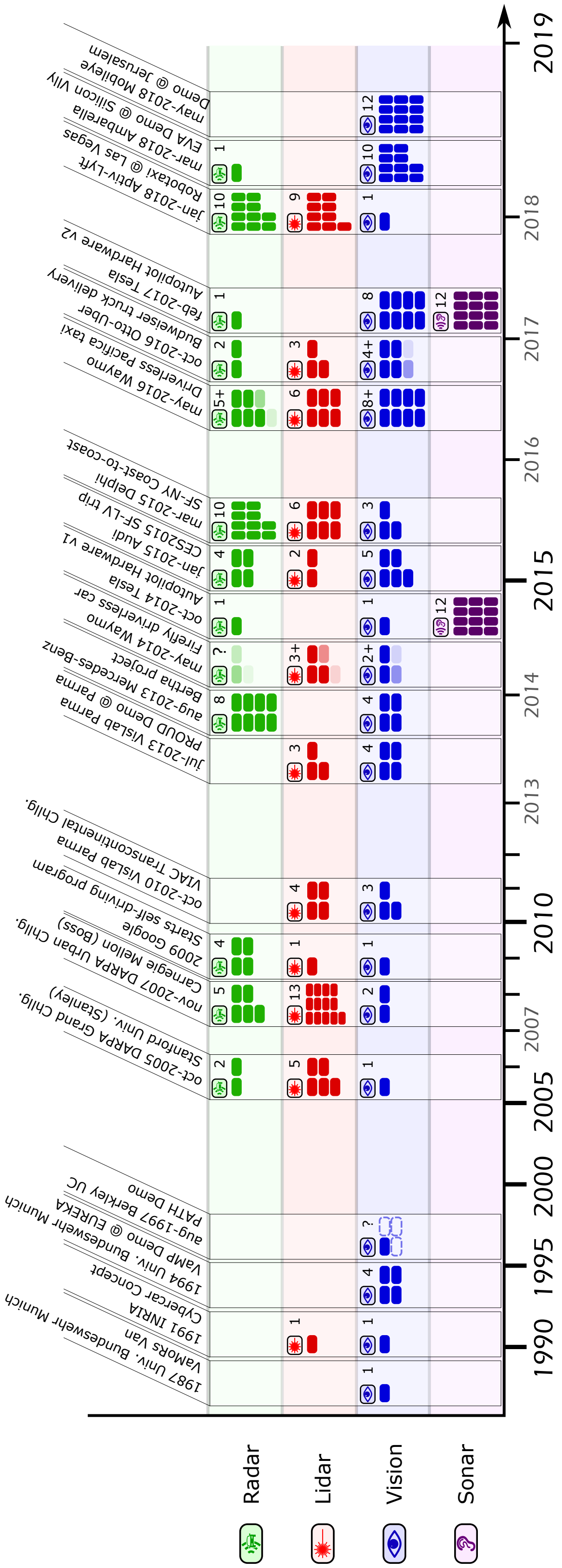

Figure 4. Timeline of relevant AD demonstrators and its sensor setup for Perception systems

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 [98], 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 [99] 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 [100], [101]. 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 Chrisler Pacifica (2016-present). Google's approach to self-driving vehicles is largely founded in 3D mapping technologies [102], 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 [103]. The leading vehicle did perception (with cameras and LiDARs), decision and control, with some human intervention for selecting the route and managing critical situations [104], and the rest of the vehicles followed it based on visual tracking and GPS points [104]. 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 [105]. It used a perception scheme similar to VIAC configuration, but relying more in cameras than 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 these companies have been founded by people coming from the DARPA experience, or have hired them to lead the project [102]. 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 founded by an engineer in Google's Street View project completed a beer delivery service with an automated truck in 2016. Uber pushed 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 [106], and Aurora company has a similar history, with people from Uber, MIT and Waymo [107].

Car manufacturers have reacted a bit slower. Apart from collaborations with research entities, as Stanford and Audi to perform the Pikes Peak ascent in 2010 (focused on control and not in perception) [108], 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 [109], with efficient algorithms processed in a heterogeneous computing platform (FPGAs, embedded processors) and new concepts as the *Lanelets* for road representation [110].

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 [111]. 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 [112,113]. After testing in real conditions [114], they presented a demo with an automated Ford equipped just with 12 small monocular cameras for fully automated driving in 2018 [115].

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 hardware version 2, 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 [116]. Its latest demo took place in Silicon Valley in 2018 [117], 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" [118]. 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, which 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. 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 comercial 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

Sensor setups in Automated Driving are usually focused on the areas relevant for the usual driving tasks: long range ahead from the vehicle, also long but no so much behind, and short-mid range in the laterals. This covers all the behavioral compentences enumerated in section 3. This plain 360 degree coverage can be insufficiente for a commercial system expected to work in the real world. Some specific challenges like critical distances (too short and too large), occlusions or bad weather conditions do not have a proper solution yet.

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

This is a problem that can be tackled by adding redundant sensors in specific positions. Some commercial 360-degree-view parking systems [78] already seem to have a good visibility of vehicle close surroudings. 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 [119–121]), 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 [89,90], where a rotating platform where 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.

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.

Intention detection Human drivers infer the intentions of pedestrians and vehicles combining subtle sensory hints with a mind model of the observed actor, and taking into account the context. Head pose, gaze direction, position of hands, or motion of arms and legs can be used to assess the awareness of a pedestrian or a driver about what is going on in a certain road area but are also indicative of intended motion direction. The steering angle of front wheels can hint if a vehicle is going to leave a roundabout or stay inside.

Many works can predict vehicle lane changes [122], risk at intersections [123] or pedestrian intentions [124,125] applying machine learning and bayesian techniques to data acquired by exteroceptive sensors. Its accuracy is sometimes limited by resolution and accuracy of sensor technologies, which cannot capture the aforementioned hints. Further sensor developments can lead to much powerful intention predictors, that will result in safer and more fluent driving algorithms.

Generalization ???

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 custumers 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, economiy an other factors. For a discussion on costs and impact of Automated Mobility services, see [126].

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 movile 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 pervious decade (2009), the most requested Advanced Driving Assistance Systems (ADAS) [127] 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 [128]. 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 coallitions 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.

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

The relevant works and demos provide a good perspective of how different manufacturers and research groups do perception tasks and wich kind of sensors they use for that purpose.

Finally, the section 5.2.1 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.

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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

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 accurance 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

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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