ASTRail

SAtellite-based Signalling and Automation SysTems on Railways along with Formal Method and Moving Block validation

D3.1 - State of the Art of Automated Driving technologies

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Legal Notice

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1 Executive summary

The ASTRail project contributes to the innovation of the railway sector by supporting research activities related to specific topics that are GNSS localization, hazard analysis of the moving block signalling system, formal methods and autonomous driving. The latter topic is the target of the activities of ASTRail WP3 and aims to provide recommendations about the technological solutions which may be exploited in the next future for enhancing autonomous driving in the railway sector.

The task T3.1 of WP3 has been devoted to the identification of the technologies which are currently employed or under development in the automotive, in the railway and in other application fields, such as agriculture, maritime and industrial, where vehicles with autonomous driving features are already available or addressed. The survey performed in task T3.1 is reported in this deliverable. Scientific literature, industrial and market solutions have been analysed to provide an overview of all cutting-edge technologies that are available.

First, the concepts, which are at the basis of the autonomous driving system, have been analysed. The most challenging and pivotal function has been identified in the navigation functionality. The navigation comprises the localization of the vehicle in the driving environment and the perception of objects in the surroundings of the vehicle. Surveying the different application fields, it has been observed that most of the technologies, which are employed for the navigation task, are nearly the same in all application fields.

The vehicle's localization is usually achieved using satellite positioning techniques that are complemented by dead reckoning methods (mainly odometry and inertial navigation) to improve the accuracy in the vehicle's localization. Significant research effort is also devoted to employ visual sensors, i.e. camera, and other perception sensors, such as RADAR or LiDAR, to identify particular features of the driving environment and to create a virtual representation. These approaches are used for a map-based localization.

The detection of objects can be achieved using several perception sensors, i.e. cameras, RADARs, LiDARs. Typically, different types of sensors are used together since most of them are complementary for characteristics in different working conditions, such as bad weather or low lighting conditions. The joint use of several sensors is a common feature in autonomous driving for both localization and obstacle detection tasks. Fusing data from different sensors can indeed provide high reliability, robustness and it can improve the results accuracy.

In both localization and obstacle detection tasks, cooperativeness among vehicles has been also considered, in particular in the automotive field. Exploiting wireless communications, a vehicle can exchange messages informing the other vehicles about its position and motion, and about potential obstacles or dangers that it identified. This cooperative approach can ease the autonomous driving tasks reducing the overall system complexity.

The information about technological solutions and related sensors, which has been gathered during this survey, will be exploited in the next tasks of WP3. In Task T3.2, the applications and characteristics of the identified autonomous driving technologies will be analysed to determine their appropriateness in the railways. Finally, in task T3.3, the assessment of the technologies will be performed to identify the most promising ones to be employed in the railway sector.

2 Introduction

2.1 Scope

This deliverable introduces the results of the survey on the state-of-art autonomous driving technologies in the automotive and other application fields. This survey has been conducted in the Task T3.1 of ASTRail WP3. The objective of the Task and of the survey is to identify what technological solutions are currently employed and/or are currently under development for enabling autonomous driving functionalities in various application fields such as the automotive sector.

Specifically, the following application fields have been considered during the survey:

- *agriculture*: autonomous tractors and agricultural robots are considered: these vehicles are employed to perform agricultural tasks in the framework of precise farming concept;
- *industrial*: Automatic Guided Vehicles (AGV), such as forklifts and carts, are the main category of industrial vehicles that are being enhanced with autonomous driving capabilities;
- *maritime*: small size surface and underwater unmanned maritime vehicles have been developed so far, they are mainly used for surveillance and discovery scopes;
- *avionic*, unmanned aircraft, both fixed-wing and rotary-wing, will be surveyed in the avionic application field;
- *automotive*: several projects for self-driving cars and other road vehicles, such buses and trucks, are currently under study;
- *railway*: this application field has been considered to keep into account the already existing automation systems in the railways, such as Automatic Train Operation (ATO) system in main lines and Communication Based Train Control (CBTC) based proprietary solutions in metro lines.

The outcomes of the survey on autonomous driving technological solutions will be the input to future Tasks of WP3. First, in the next Task T3.2, implementation characteristics and operation conditions of the automotive will be analysed to evaluate which of them are also valid in the railway sector. Afterwards, in the successive Task T3.3, the autonomous driving technologies, that are most suitable for the adoption in the railway field, will be evaluated and ranked according to their potential effectiveness in improving autonomous driving in the railway system.

2.1.1 Autonomous Driving Context

The autonomous driving context of each application field and the enabling technologies, together with the required sensors, are both covered in this survey. These aspects are indeed important for the understanding of the developed autonomous driving solutions.

The context is mainly related to the characteristics of the environment where the vehicle circulates and to the final scope of use of the vehicles. The environment can strictly condition the implementable autonomous driving solutions, due to specific requirements and constraints that are present. For example, technical solutions for underwater vehicles or for industrial carts can hardly rely on Global Navigation Satellite System (GNSS) technology. This aspect can be of interest since similar solutions may be employed by trains to cover tunnels.

Other requirements are related to specific regulations that govern the operations and the interactions of all actors in a given transportation environment. In the case of the automotive fields, self-driving cars and all other road vehicles are required to respect road regulations. This means that they have to perform manoeuvres that are compliant with such regulations. Similarly, ships have to follow specific rules when approaching other maritime users. Autonomous driving solutions need then to make the vehicle able to perform such manoeuvres.

The final scope of use of autonomous driving vehicles impacts also on the requirements that the solutions should meet. For instance, autonomous tractors are used to perform specific agricultural tasks, thus high accuracy on the vehicle localization is required, but low speeds are acceptable. Instead, road vehicles and trains should achieve significantly higher speeds, while keeping high-precision positioning and ensuring high-level of safety for on-board passengers.

2.1.2 Enabling technologies and sensors

This first survey details the technologies that have been used for autonomous driving solutions. In particular, their characteristics and employed sensors are analysed and described. The requirements and the performance of each technology are considered.

An overview on the information exchanges is also provided since communication technologies provide a significant contribution to the implementation of effective autonomous driving solutions. Intra-vehicle communications, i.e. among sensors and controller modules on board, are considered in the same way as for communications among vehicles or between vehicle and fixed infrastructure.

2.2 Methodology

Different types of sources have been exploited during the survey. Academic research, such as scientific conference papers, journal manuscripts and (mainly European) research projects, has been considered. Outcomes of industrial research and development have been taken into account as well. In this case, prototypes and concepts, custom and commercial solutions have been searched and analysed.

A systematic literature review approach has been adopted during the survey. Different search engines have been exploited, in particular IEEE Xplore Digital Library, Google Scholar, Elsevier's Scopus as scientific web engines, while Google as web engine for searching commercial products and solutions. Specific strings have been identified to search for autonomous driving technologies and solutions. The strings "autonomous driving", "automatic driving" together with terms such as "technologies", "solutions" or "products" have been searched jointly with terms identifying the specific application fields, such as for example "automotive", "maritime", "agriculture". From the documents identified by this approach, additional searches have been performed, considering more relevant and frequent keywords. Finally, the references contained in these documents and manuscripts published in the same conference or in the same journal issues have been also taken into account.

The first selection of scientific documents has been performed evaluating if the manuscript provides basic details on the technologies and on the sensors employed for autonomous driving. The selected documents have then been rated considering the level of details introduced for the technological solution, the realization of practical experiments, the year of the study and the advance of the proposed solution with respect to the state-of-the-art. Commercial, industrial or non-scientific documents have been rated considering the availability of technological details on the proposed autonomous driving solutions.

The present survey is not comprehensive of all research studies, prototypes or products that target the development of autonomous driving and it is not aimed at that. This survey aims to identify all possible technologies employed for autonomous driving and it refers to part of the available literature and public documentations as support to the technical concepts.

2.3 Deliverable organisation

The deliverable is organized as follows. In Chapter 3, the concept of autonomous driving is introduced. It is indeed essential, for understanding the technologies and the outcomes of the survey, to know which the main steps are in the process of autonomous driving. The basic technologies, which are commonly employed in the autonomous driving solutions for all application fields, are described in Chapter 4. The survey highlighted that similar technical approaches have been used through all application fields. This Chapter aims thus to explain these approaches once avoiding repeated explanations through the document.

The following chapters are dedicated to each of the previously mentioned application fields, that is Chapter 5 for the agriculture, Chapter 6 for industrial AGVs, Chapter 7 for the maritime sector, Chapter 8 for unmanned aerial vehicles, Chapter 9 for the automotive sector, Chapter 10 for current automatic driving solutions in the railways. For each application field, details about the context, specific technologies and sensors used will be provided.

The outcomes of the survey are resumed in Chapter 11 where conclusions are also drawn.

3 Autonomous driving concept

A **fully autonomous** driving vehicle consists in a vehicle that can drive in the targeted environment without intervention of a human driver. This kind of vehicle needs to implement all required functionalities that permit to safely drive the vehicle to the destination.

The main functionalities for an autonomous driving vehicles are [1]-[2]:

1. *Trajectory Planning*; it determines the path that the vehicle should follow; the trajectory is typically made by a set of waypoints between the source and the destination of the vehicle jointly with the speed that the vehicle has to sustain between each two waypoints; the definition of the trajectory is strictly dependent on the physical characteristics of the vehicle and of the environment in which the vehicle circulates, in addition to all constraints deriving from the regulations present in the driving environment; for example, the trajectory planner needs to take into account the maximum curvature and velocity that the vehicle can sustain, the speed limits and the allowance to perform specific manoeuvres;
2. *Navigation*; it is the process of determining the state of the vehicle, that includes the position of the vehicle, the speed, the acceleration, the heading, the distance travelled; the information available is strictly related to the sensors employed;
3. *Guidance*; this functionality refines the planned trajectory taking into account where the vehicle is estimated to be (*Navigation*) and where the vehicle should be (*Trajectory planning*); the guidance determines thus the reference trajectory in order to minimize the position error and it provides the new trajectory to the control functionality;
4. *Control*; the control functionality implements the reference trajectory defined by the *Guidance*, this consists in determining the forces to be produced by each actuator to implement the reference trajectory, the *Control* determines these forces and it sends the appropriate commands to the actuators.

3.1 Trajectory planning

The research topic of trajectory planning has been widely targeted by the research community. In particular, trajectory planning has been widely targeted in the robotic research field. Trajectory planning mainly consists in the definition of mathematical algorithms and analytical methods that identify the best feasible path between two end points given a set of constraints and of evaluation metrics.

Most common ones are shortest paths algorithms such Dijkstra’s algorithm. Several surveys are available in the literature targeting the trajectory and the motion planning specifically for vehicles. We refer to [3]-[5] for detailed descriptions of the algorithms and methods used in different transportation sectors.

The trajectory planning is of partial interest in the railway transportation sector. Trains’ trajectory are constrained by tracks and the position of railway switches is defined by the railway control system and not by each train. The definition of the velocity in the trajectory is defined by known line profiles and limited by the presence of other train on the route. It is also strictly related to the timings defined by the centralized control system. Furthermore, trajectory planning is mainly related to mathematical operation research rather than to technology development. This survey thus does not focus on trajectory planning due to previous motivations.

3.2 Navigation

The *Navigation* is in charge to sense the vehicle state and the environment in order to provide information to the guidance system. The state of the vehicle is determined using the available sensors information and it comprises the position, the speed, the heading and also other vehicle’s properties such as the acceleration. The *Navigation* is also in charge to detect obstacles in the surrounding of the vehicle.

This survey details the characteristics and performance of the technologies with the enabling sensors that can provide input to the *Navigation* functionality. In autonomous driving, most of the effort is indeed devoted to search and to develop technological solutions that can effectively sense the state of the vehicle and the environment.

3.3 Guidance and Control

In order to better explain the intended goal of the present deliverable, it may be worth recalling the distinction between *Guidance* and *Control* in the railway sector.

In the railways, the *Guidance* is essentially limited to the definition of the speed that the train should target according to external inputs, such as speed limits, programmed travel times, obstacle detections, specific manoeuvres and other external inputs from sensors. As explained before, the planning of trajectories in trains is basic, since trains' journey are planned and maintained by centralized systems.

The *Control* functionality, conversely, refers to a controller module that is based on specific mathematical models of the real-world systems. Indeed, the Control Theory deals with the specification of mathematical control system models and on the development of related controller techniques. The control system models are very specific since they need to model the real-world physical system characteristics; thus, the controller techniques strictly depend on the system modelling and on the available actuators.

In the specific area of vehicles' control, the objective of the controller is to specify which forces have to be applied to the actuators to minimize the difference between the real and the planned trajectories. Train control mainly consists in maintaining the train speed to the speed specified by the *Guidance* (and monitoring the safety of operation). The Automatic Train Protection (ATP) system provides a basic implementation of such functionalities (*Guidance* provides the speed limits and *Control* applies emergency brakes if the speed limit is exceeded). ATO system implements all these functionalities increasing the grade of the responsibility of the system depending on the Grade of Automation. Detailed description of ATP and ATO system is provided in Chapter 10.

Guidance and *Control* are also strictly related to the sensors that are available on-board of the vehicle and at infrastructure-side. At the moment, some sensors are already used for estimating the motion of trains. However, it is expected that additional sensors will be used to enhance autonomous driving in the railway sector, in particular for what concerning obstacle detection.

For the sake of clarity, **the intended goal of the ASTRail project is to assess sensors and technologies adopted for autonomous driving in other domains and indicate the most promising ones for the railway sector**.
Concerning the specificities of *Guidance* and *Control* functionalities they represent a next step of the study and fall outside the scope of the project. Consequently, in the following of the document, we will not provide further details on *Guidance* and *Control*. However, for sake of completeness, we refer to [5] and [6] for a broad overview of the main control techniques for autonomous vehicles.

4 Technologies for autonomous driving

In this Chapter, the main technological solutions for the *Navigation* functionality are described. As introduced in Chapter 3, the *Navigation* concerns all those methods that provide the motion state of the vehicle (e.g., speed, heading, acceleration, …) and information about the surrounding environment. The *Navigation* functionality is the major challenge in autonomous driving solutions and most of the research focuses on this issue.

The information gathered by sensors is used to target two main objectives: the *localization* of the vehicle and the *perception* of the surrounding environment to detect possible obstacles and driving surface. This Chapter describes the state-of-the-art technological solutions that are proposed and employed to achieve the aforementioned objectives. In Section 4.1, the main methods for localization are presented, while the perception topic is discussed in Section 4.2. Lastly, in Section 4.3 the importance of the multi-sensors data fusion approach is introduced.

4.1 Localization

The localization of the vehicle can be distinguished in two main categories [7]:

- *Absolute* localization: define the position of the vehicle within a global reference frame;
- *Relative* localization: determine the incremental vehicle's position based on the measured motion of the vehicle.

These two approaches are not mutually exclusive, but typically they are both exploited. Integrating the results of several localization techniques exploiting multi-sensors data fusion approach can increase the accuracy in the positioning. Further details on multi-sensors data fusion are provided in Section 4.3.

4.1.1 Absolute localization methods

4.1.1.1 Beacons-based

In this method, the vehicle relies on active beacons that are transmitted by anchors nodes. The distance or the direction of incidence (i.e. angle) between the vehicle itself and the anchor can be measured and, based on this information, the position of the vehicle can be computed using trilateration, if distances are known, or triangulation, if angles are known, techniques [7]-[9]. If the vehicle knows the absolution position of the anchors, it can estimate its absolute position. GNSS or Mobile Positioning Systems [10] are examples of beacons-based localization methods.

Trilateration is the geometric process of determining the position of a target point exploiting the measured distance between the target point and three anchors. The target point is located on the circumferences of the circles having as centre respectively each anchor and radius equal to the measured distance between the target point and each anchor. At least three anchors are required to univocally determine the position of the vehicle in a two-dimensional space. Indeed, three circles intersect in just one single point that corresponds to the position of the target point. Different mathematical methods can be used to solve the geometric equations associated to the trilateration problem.

The vehicle can compute the distance from itself to the each anchor using ranging techniques such Time of Arrival or Time of Flight [9]. In these techniques, the distance can be computed using the measured time for the signal propagation and the signal velocity. These techniques can be further differentiated if the time measured for the propagation corresponds just to the time to cover the distance from the anchor to the vehicle, i.e. one-way Time of Arrival, or it is the round-trip time of the signal, i.e. two-way Time of Arrival.

The triangulation technique instead exploits the geometric properties of triangles in order to determine the position of a target point. Triangulation is based on trigonometric operations that allow to determine the position of a target point based on the knowledge of the angle of incidence between the target point and the anchors nodes. In the case of a two-dimensional space, two bearing lines and the locations of anchor nodes or the distance between them are required to univocally determine the position of the target point.

The angle of incidence corresponds to the angle between the propagation direction and some reference direction known as orientation [11]. The measurement of the angle between the vehicle and the anchor can be performed using an array of sensors. The array is used to receive a single signal and to determine the differences in arrival time, amplitude, or phase that can be then used to determine an estimate of the arrival angle. Sensors can be antennas for wireless based systems or microphones in case of acoustic measurements. Other possibility is to use a rotating sensor that can measure the angles of incidence between the vehicle and the anchor [7], [8].

4.1.1.2 Landmarks-based

This method is based on the identification of specific and known features, i.e. landmarks, of the surrounding environment. The vehicle needs to identify the landmarks and to determine its position based on the relative position of landmarks with respect to itself [7]. The vehicle must know the characteristics of landmarks in order to be able to identify them and it must know their position as well. Same localization techniques of beacons-based method can apply. The landmarks can be either artificial or natural. In both cases, they need to be easily identifiable by the sensors of the vehicle.

Natural landmarks are all those objects or features that are already present in the navigation environment of the vehicle and their scope is not related to the navigation of the vehicle. They can also be "man-made" and, in that case, they are more effective since easier to be recognized. The employment of natural landmarks is more suited in highly structured environments such as factories or more in general buildings. Examples of good natural landmarks are corner, edge or long straight walls. Natural landmarks are typically identified using vision-based system. The vehicle needs to be equipped with a vision sensor, e.g., a camera, and it has to process the acquired images using vision processing techniques in order to detect the landmarks and to match them with the list of known ones.

Artificial landmarks are instead specific objects or markers that are installed in the navigation environment of the vehicle and they have the unique scope to assist the vehicle in the localization process. These are easier to be recognized since the exact size and shape are known in advance and they are designed to be easily identifiable. Positioning systems using artificial landmarks can be exploited either using vision processing either exploiting the reflectiveness of specific artificial landmarks. In the latter case, sensors such as RADAR and LiDAR, can be used to recognize the artificial landmarks. Other types of artificial landmarks can also consist in barcode or QR-code that permit to provide enhanced information to the vehicle [7], [12].

Another artificial landmark-based navigation is the line navigation where the vehicle needs to follow a physical line [7]. The line navigation system can be based either on an electromagnetic guidance using an electromagnetic sensor or on a visual guidance using a camera and image processing techniques. The line can indeed be seen as a continuous landmark.

4.1.1.3 Map-based

The vehicle locates itself comparing the sensed environment with a global map or model of the navigation environment. The matching between the representation of the current environment and the global maps allows the localization of the vehicle [7], [8], [13]. In this method, it is essential that a sufficiently accurate map is available and also that the navigation environment is enough stable in order to guarantee that the map is updated. The map is assumed to be built before navigation and available to the vehicle. Other map-based methods are instead developed considering that the vehicle itself builds the map. In those cases, an absolute positioning cannot be achieved. Further details on these relative maps-based localization methods are provided in Section 4.1.2.

Vision sensors, RADAR or LiDAR can be used to sense the environment. Typically, more sensors are used and the gathered information is fused together to provide an enough accurate representation of the current real environment. For example, monocular camera (i.e. 2D sensor) can be used for achieving a good spatial resolution of the scene easing the objects and features recognition, while RADAR or LiDAR sensors can be used to provide accurate information on distances.

4.1.2 Relative localization

The relative localization, also known as Dead Reckoning, is used to determine localization of the vehicle considering the motion of the vehicle, i.e. speed and direction, on a defined time interval and given a previous known position. An absolute localization can be achieved with dead reckoning if the previous known position is referred to an absolute reference frame.

The accuracy of the vehicle positioning is strictly related on the precision of the used motion sensors. Furthermore, the dead reckoning is an iterative process and positioning errors accumulate over time. Dead reckoning systems can thus ensure sufficient performance only on short time periods and a recalibration of the absolute position is required from time to time. These methods are indeed often used jointly with other absolute localization methods.

Several dead reckoning methods are available. They can be mainly distinguished by the motion sensors that they used. In the following of this Section, an overview of the main motion sensors systems used for dead reckoning is provided.

4.1.2.1 Wheel Odometry

The most common and used dead reckoning method is the wheel odometry [7], [8], [14], [15]. This method is based on the estimation of the movement of a wheeled vehicle counting the number of revolutions of the wheels. Exploiting the vehicle kinematic equations, it is possible to translate the number of revolutions (i.e., velocity) and the steering angle of the vehicle to motion information. The rotary encoders are the main sensors used in wheel odometry. Rotary encoders can provide information about the motion (incremental encoders) or the steering angle (absolute encoders) of the vehicle.

This method is commonly used since it is simple and practical. However, performance are affected by incremental errors that accumulate over time. Displacement and orientation errors are accumulated at each position estimation and thus they proportionally increase with the overall travelled distance. These errors can be either systematic (wheels misalignment, uncertainty on the wheel diameter, differences in the contact surface of the wheel) either non-systematic errors (wheel spinning or slippage due to bad ground conditions, uneven ground surfaces).

4.1.2.2 Inertial navigation

The inertial navigation is a self-contained navigation method that can provide the position, the speed and the direction of the vehicle knowing the previous position and exploiting inertial principles such as acceleration and angular velocity or other forces related to the inertial space [16]-[17]. Most common sensors are the accelerometers as motion sensors for acceleration forces and the gyroscopes as rotation sensors for angular velocity. The inertial navigation involves to sense accelerations in each of the three directional axes and to integrate these measurements over time to derive the velocity and the position of the vehicle. A gyroscopically stabilized sensor platform is used to maintain consistent orientation of the three accelerometers throughout this process [7].

Three gyroscopes and three accelerometers are normally combined in an Inertial Measurement Unit (IMU) [16]. An IMU can provide sufficient information to locate relatively to an inertial space given initial conditions (i.e. position, direction and speed of the vehicle). Integrating one acceleration measurement provides the velocity of the vehicle, a second acceleration integration can provide the position, while the correct direction can be found integrating the measured angular velocity. In the case that the vehicle is close to the Earth, it is required to compensate the gravitation, and rotation of the Earth that is not an inertial system. The equations integrating the gyroscopes and accelerometers measurements into velocity, position and direction are known as navigation equations. An IMU and a processing system solving the navigation equations is named an Inertial Navigation System (INS).

The INS is affected by errors accumulation over time since it is based on iterative integration of acceleration and angular velocity measurements that are affected by errors as in the wheel odometry. However, advantage of INS is to be not sensitive to wheel slippage and to ground conditions. INS presents thus a drift in the position, velocity and orientation. Furthermore, high-accuracy INS involves very expensive equipment. A possibility to limit the drift is to help INS using other sensors, which provide direct measurements of specific quantities, such as pressure sensor for depth/height or magnetic compass for direction [16]. Alternatively, a periodic correction of the INS considering other absolute localization methods, such as GNSS system, is required.

4.1.2.3 Doppler RADAR

Other dead reckoning method is based on the Doppler Effect in which there is a shift in frequency that can be observed when the radiated energy reflects on a surface that is moving with respect to the emitter [7]. A Doppler RADAR can thus measure the real speed of the vehicle without being sensitive to ground and wheels conditions, eliminating wheel spinning and slippage errors.

The Doppler RADAR is typically used in the maritime and avionic transportation sectors where it can provide accurate velocity measurements without introducing errors due to unknown environmental conditions such as ocean or air currents.

4.1.2.4 Visual odometry

Another method to estimate the motion of the vehicle is based on vision processing. The visual odometry consists in determining the motion of the vehicle by analysing sequential images taken from a camera that is on-board the vehicle and using image processing techniques to estimate the motion. The estimation is performed considering the world reference frame and a previous position is required to determine the new position [13], [14].

The visual odometry can be divided in three main steps that are i) the establishment of matches between two consecutive images, ii) the removal of the outliers in the images matching, iii) the estimation of the motion between the two frames. The motion estimation is performed considering the matches between two consecutive images. The trajectory of the camera, and thus of the vehicle, can be defined concatenating all these single movements. Different approaches can be used in visual odometry. The most common ones are feature tracking, appearance-based or a hybrid approach. Detailed description of these methods are provided in [13], [14].

Different types of camera can be used for visual odometry. Monocular cameras are the less expensive, but they can provide only two-dimensional representation of the environment, while a three-dimensional representation have to be computed starting from the two-dimensional one. Other types of camera are stereo and omnidirectional cameras which can provide accurate three-dimensional representations, but at higher equipment costs. Extensive analysis of cameras' advantages and drawbacks is presented in [14].

4.1.2.5 Simultaneous Localization And Mapping (SLAM)

Simultaneous Localization And Mapping (SLAM) is a relative localization technique in which the vehicle, while navigating in an unknown environment, i.e. without having a map or without knowing the position of landmarks, builds a map of the surrounding environment and it uses this map for the navigation and for locating itself within the environment [13], [14], [18].

The main task of SLAM is to build the map of the environment exploiting the information received from the available sensors. Main steps of SLAM are the identification and extraction of landmarks in the environment, data association, state estimation, state update and landmark update. Detailed description of SLAM process can be found in [18]. Typically, multi-sensors data fusion is exploited to enhance the availability and richness of environmental information. Sensors used are perception sensors, such as RADAR, LiDAR or cameras, and also motion sensors, such as wheel encoders.

Recent SLAM techniques are mostly based on vision sensors system. Vision-based SLAM techniques are based on the same techniques employed for visual odometry. However, the scope of SLAM is far more complex since it is used to build a map, instead of only estimating the vehicle's motion. The result is a more accurate three-dimensional representation of the navigation environment, but at higher computational cost.

4.2 Perception

Main task of the perception sensors system of the vehicle is to detect obstacles in the surrounding of the vehicle. It is indeed required that every obstacle is identified and located allowing the vehicle to properly refine its trajectory. The challenge of obstacle detection is related to the complexity in characterizing the features of the obstacles. Shape, size, colour and position of obstacles can significantly vary and no information about obstacles' features can be ensured a priori. Further issue of obstacle detection is that some obstacles can be moving and most of them, such as vehicles, bicycles, pedestrians, animals, has an unpredictable behaviour [6], [19].

Other task of the perception system is to identify the surface over which the vehicle can drive. In structured environment, such as roads, the system has to detect the road surface and the correct driving zone, i.e. the lanes. Further task in structured environment is the identification and recognition of traffic signs and of road markings. In unstructured environment, driving surface detection is instead more complex since it is not possible to exploit the presence of asphalt or road lines [19].

Algorithms for obstacles detection are strictly connected to available sensors of the perception system. These sensors are exteroceptive since they sense surrounding environment and they can be divided in two main categories: i) passive and ii) active sensors. This classification is mainly related on the mode that sensors adopts to gather information from the environment. In the specific, passive sensors exploit the energy from the environment itself, while active sensors illuminate the environment to execute the detection.

Another way to identify potential obstacles is to rely on the cooperation among vehicles and other actors of the environment. Obstacles and vehicles' state (i.e. position, speed, direction) can be communicated among all vehicles increasing the range of obstacles detection and allowing to know in advance the trajectory of other vehicles.

4.2.1 Passive sensors

The passive sensors exploit the energy already present in the environment and they can be used only if natural or artificial light sources illuminate the environment. Passive sensors are basically visual cameras. They can operate at different wavelengths according to the target environment and scope of use. Cameras working at visible light can provide high level of detail of the environment, while infrared cameras can be effective at low light conditions to detect all warm objects [19].

Drawbacks of cameras is the sensitiveness to weather and lighting conditions. Visible light camera are particularly affected by darkness, backlighting and shadows making more difficult and less precise the obstacles recognition. Infrared cameras are not affected by lighting conditions, but their performance changes in specific weather condition. In case of heat, rain and fog the infrared cameras' performance are worse since these weather phenomena affect the heating emissions of objects. Advantage of passive sensors is their relatively lower cost with respect to active sensors. The higher cost of active sensors is mainly due to the fact that they have to emit signals to illuminate the scene in order to be able to sense the environment.

The obstacles detection process using passive sensors requires that image processing techniques are applied to the gathered images/videos of the surrounding environment. Image processing needs first to detect possible obstacles or regions where obstacles can potentially be present. Afterward, all potential obstacles are analysed to identify the possible type of the obstacles. Image processing techniques are strictly connected to the types of cameras that the vehicle is equipped with.

Main type of cameras are monocular camera, stereo camera, omnidirectional camera. In monocular cameras only two-dimensional information about the environment can be sensed and the three-dimensional structure of the environment has to be computed starting from two-dimensional bearing data [20]. Stereo cameras are instead built to determine a three-dimensional description of the environment. Stereo cameras are based on the same principle of human vision. A stereo vision system is made by two cameras that are positioned at a known distance and that take pictures at the same time. Based on the geometry model of the stereo cameras system, it is possible to determine the three-dimensional geometry of the environment. In particular, exploiting the two points of view, the depth-map can be computed comparing the distances from the object to the cameras system. The depth-map consists in a two-dimensional image in which the colour of every pixel represents the distance from that point to the camera [21]. An omnidirectional camera can provide accurate three-dimensional environment perception since it is a camera with a 360-degree field of view in the horizontal plane, or with a visual field that covers a hemisphere or (approximately) the entire sphere [22].

Camera systems, which can provide a three-dimensional representation of the environment, can be more effective in identify and characterize potential obstacles. However, these systems are typically more expensive than monocular ones.

4.2.2 Active sensors

Active sensors illuminate the surrounding environment with energy and they sense the energy reflected by the nearby objects to create a three-dimensional representation of the environment. The sensors are differentiated considering the type of signal (i.e. the emitted energy) that they use to illuminate the scene. Three main categories of active sensors are i) **RA**dio **D**etection **A**nd **R**anging (RADAR), based on emission of radio waves, ii) **Li**ght **D**etection **A**nd **R**anging (LiDAR), exploiting light emission, iii) **SO**und **NA**vigation and **R**anging (SONAR), in which sound propagation, typically ultrasonic waves, is exploited. The performance and the range significantly vary according to the type of sensor. In particular, light and weather conditions have a different impact on each type of sensor. For example, sun light can interfere with the operations of LiDAR. In the following of this Section, an overview of the main characteristics of these sensors is provided.

One significant advantage of active sensors with respect to passive ones is the capability to provide some direct measurements of the distance and of the size of the objects present in the environment. This can be achieved by measuring the round-trip time of the signal emitted and by quantifying the signal reflection. The computational resources required are then lower than in the case of passive sensors. However, some drawbacks are also present in active sensors. Main disadvantages are the higher cost, the lower spatial resolution and the slow scanning speed of the rotational mechanic parts.

4.2.2.1 RADAR

RADAR-based sensors can operate at long ranges and they are not significantly affected by light and weather conditions, such as for, rain. RADAR, exploiting the Doppler Effect, can also provide speed measurements. Modern RADAR system for road vehicles do not employ a rotating antenna, but they are based on a patch antenna with digital signal processing-based pattern beam-forming methodology to measure azimuth angle [23].

Main drawback of RADAR is its performance in complex scenarios. Indeed, performance of RADAR is strictly related to the reflectiveness and consequently on the radar cross section of objects. For example, vehicles can be easily identified since they are made mainly of metal surfaces that are good radar reflectors. Instead, pedestrians are more difficult to be identified since typically are scarcely reflective to radio waves. The RADAR cross section is thus typically smaller than that of the vehicles (between 0.2-2m^2 with respect to 10m^2) making them more difficult to be identified [19].

4.2.2.2 LiDAR

LiDARs, or laser-scanners, are based on a rotating laser that sends multiple beams of light at infrared wavelength. The light is reflected by non-absorbing objects and the LiDAR can measure the range and returned intensity for each angle creating a three-dimensional map of the environment [6], [19], [23]. Sunlight and some weather conditions, e.g., rain and fog, can impact on the performance of LiDAR sensors since they work on infrared frequencies. Sunlight can interfere with the reception of reflected light beams, while fog and rains can create multiple echoes affecting the performance.

The information gathered by the LiDAR consists in a sparse cloud of three-dimensional points that represents the surface of the objects having reflected back the LiDAR light beams. Point clouds, features and grids are the most common representations of the points. The cloud of points requires to be processed in order to extract useful information. First, the segmentation of the points' cloud is performed. In the segmentation process, points are clustered in several homogeneous groups. Classification of clusters is then performed to categorize them. The analysis of each cluster permits to identify some characteristics and to determine if a given cluster of points represent a vehicle, a pedestrian, an obstacle or the road surface [6]. The result is a very accurate three-dimensional representation of the environment achieving a better performance than RADAR sensors. However, LiDAR have the drawbacks to be usually more expensive and to require additional packaging space [23].

4.2.2.3 SONAR

SONAR sensors utilize sound waves, which are above the range of human hearing, to determine the distance to objects in the environment. The working principle is that the sound wave is reflected from the objects in range and the frequency of the return pulses indicates the distance from the sensor to the object. Indeed, according to the object that the sound wave encounters, the reflected wave can have different degrees of phase change and amplitude modulation [23].

SONAR systems are usually very cheap, but their performance is strongly affected by the characteristics of the medium, such as temperature, humidity and environmental conditions, that sound waves need to traverse. Ultrasonic sensors are typically more affected than RADAR to blockage due to the physic characteristics of sound propagation. They are generally used for applications in which a limited operating range is allowed [23].

4.2.2.4 Infrared-equipped visual camera

A more recent type of active sensor is represented by visual cameras equipped with infrared dots projector. These cameras illuminate the environment with frequency modulated infrared light and they can determine the depth information for each pixel by measuring the phase shift of the reflected infrared light. Advantage of this type of camera is that it integrates the good scene resolution of visual sensors with the accurate distance estimation of active sensors. Drawback is its typical short operating range [24].

4.2.3 Cooperative

The cooperation among vehicles and other actors of the environment, such as bicycles, pedestrians or fixed-infrastructure, can facilitate the identification of obstacles and other potential hazards. The cooperation is feasible only if inter-vehicle communication is available. Vehicles can exploit wireless communication technologies to create vehicular networks, where vehicles' state and other information about the perceived environment, can be exchanged [25].

Vehicles can share their motion state (i.e. position, velocity and direction) and possibly their expected trajectories. This allows to predict dynamic changes of the environment and possible conflicts in the trajectories can be solved in advance [6]. Other advantages of inter-vehicle communication is the possibility to know in advance obstacles that are not in the range of the perception sensors and the availability of more environmental information that can facilitate and increase the accuracy in the detection of obstacles. Further advantage is the improvement of vehicle position accuracy that can be achieved exploiting cooperative relative positioning methods [25].

4.3 Multi-sensors data fusion

The data fusion of information from multiple sensors has the main objectives to increase accuracy, availability and reliability. Each sensor presents advantages and drawbacks and sensors data fusion permits to mitigate the drawbacks, while exploiting their strengths [23].

Improvement of the accuracy, availability and reliability can indeed be achieved thanks to sensors data fusion since information from sensors is combined achieving a mutual verification of results and information backup in case of failure. Further advantage produced by multi-sensors data fusion is the cost effectiveness. Several cheap sensors may effectively substitute one highly accurate and expensive one [19].

Multi-sensors data fusion approach can be resumed in the following main concepts [19]:

- *Redundancy*; several sensors gather the same information in order to have more measurements of the same characteristics and a backup in case of failure; reliability and accuracy can in this way be improved since different type of sensors may perform differently in particular environmental conditions; for example, LiDAR performance is affected by rain and fog, while RADAR sensors are not;
- *Complementary*; different type of sensors gather different type of information, both related to different sensed areas of the environment and to different sensing capabilities; information fusion permits to achieve a wider and more accurate environmental description; for example RADAR can provide very accurate distance information, but low scene resolution and vice versa for monocular vision system;

- *Cooperativeness*; fusing information from different sensors can allow to determine information that otherwise cannot be obtained by a single sensor; for example, the position of the vehicle can be computed using three range measurements.

Several approaches for multi-sensors data fusion have been proposed for improving localization and objects detections. Broad overview of the most common approaches can be found in [6], [25]-[27].

5 Autonomous vehicles in agricultural environment

Autonomous driving in the agricultural environment has been developed to ensure accurate positioning and guidance of tractors across agricultural fields. High accuracy in the positioning is essential since autonomous tractors have to conduct specific agricultural tasks (e.g., harvesting, seeding, weed detection …) with the appropriated tools that have been also automated [28], [29].

The final scope of autonomous vehicles in the agriculture is thus not limited to navigation, but also to the execution of specific agricultural tasks. The complexity of autonomous driving is further increased since autonomous driving task and agricultural related actions have to be performed simultaneously to guarantee effectiveness in the results and safety to all actors involved. The autonomous tractor can then be defined as made by the autonomous vehicle subsystem and the autonomous implement subsystem. Due to the additional tasks and to the complexity of the mission, autonomous tractors are typically equipped with a larger number of specific sensors and actuators. Overview of required sensors and actuators for both autonomous vehicle navigation and autonomous agriculture implement is shown in Figure 1 [28].

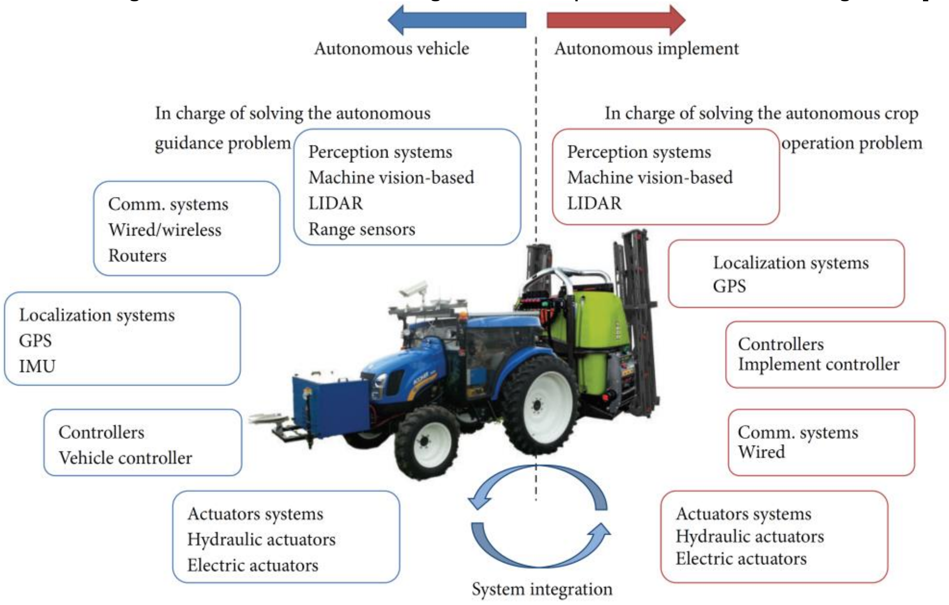


Figure 1 – Examples of sensor and actuation systems for autonomous tractors [28].

The complexity of autonomous driving in agriculture is further increased by the specific environment that agricultural fields represent. Indeed, autonomous tractors are required to navigate in rough and unstructured environments. Agricultural fields can indeed significantly vary for geometry, appearance and ground conditions and no artificial structures to facilitate the vehicle navigation are usually present. Tall grass, fallen leaves and terrain roughness can be erroneously identified as obstacles, while other environmental features, such as dirt roads, trees or bushed, cannot be properly identified. The perception system of autonomous tractors needs to characterize the unknown and unstructured environment by properly identifying obstacles and drivable surfaces [30], [31].

The main challenges, that autonomous vehicle for the agriculture need to deal with, can then be resumed in the following ones [32]:

- agricultural fields have very large operating surfaces;
- the ground surfaces of fields can be uneven;
- wheel slippage can be significant for particular ground conditions and specific operations;
- sensors performance may be affected by environmental and weather conditions, e.g., rain, fog, dust;
- low-cost systems are required to foster the use of autonomous driving vehicles for agricultural applications, in particular in the case of small fields.

In the following of this Section, localization and obstacle detection solutions are respectively introduced in Sec. 5.1 and in Sec. 5.2. Sec. 5.3 describes the communication technologies that are commonly used in autonomous tractors and Sec. 5.4 presents the standard related to safety aspects in autonomous agriculture. Developed prototypes and a first concept of autonomous tractor are described in Sec. 5.5.

5.1 Localization

Most common localization systems employed in autonomous tractors are mainly based on dead reckoning, in particular odometry and inertial navigation systems, and on absolute positioning exploiting GNSS technologies. Dead reckoning methods and GNSS are usually fused together in order to improve the vehicle localization [28], [29], [31], [33], [39].

Dead reckoning methods can be very accurate and robust on short periods. Main drawback is that odometry suffers significantly from phenomena like sensors drifting and wheel slippage. Some works have been dedicated to improve the accuracy of dead reckoning in the agriculture by developing model related to the measurements of the torques applied to the wheels in case of slippage [33]. However, odometry and inertial navigation are typically used together since it has been demonstrated that inertial navigation can be particularly effective to detect the wheel slippage [29].

GNSS technologies, typically GPS (Global Positioning System), are used to provide absolute localization of the vehicle. Several works consider to employ advanced GPS systems characterized by high accuracy, such as Differential GPS (DGPS) or Real-Time Kinematic GPS (RTK-GPS) [29], [31], [33], [35].

In DGPS, the signals, which are received from the satellites, is corrected with the signal of a GPS reference receiver that is positioned in a well-known location. This technique can improve the localization accuracy since it can remove errors due to satellite ephemeris and clock errors. Several implementation of DGPS are available and they mainly differ from the area of coverage of the GPS reference receiver. A wide-area DGPS can provide an accuracy in positioning of less than 2 meters, that is not sufficient for some agricultural tasks that require usually an accuracy of less than one decimetre [35].

RTK-GPS can ensure a better precision achieving centimetre-level accuracy. RTK-GPS is based on a process that exploits a second receiver located in a known point of the field or nearby to correct the GPS data signal received from the satellite. The drawbacks of this approach is the limited coverage (around 10 km between the vehicle and the fixed receiver) and the high costs of the system [33], [35]. However, it seems that their price is decreasing [33].

Other localization methods that have been suggested for use in the agricultural environment are based on artificial landmarks methods, exploiting sensors such as LiDAR and RADAR, in particular millimetre-waves RADARs [32], [33]. However, laser-based methods have significant drawback on rough and uneven surfaces since the tilt of the vehicle from the horizontal causes the laser beam to not properly sense the environment. A solution can be to diverge vertically the laser beam, but this reduces the operating range. Some solutions are to deploy lasers in the field and to install the reflective beacons on the vehicles [32]. Other approach is to complement the LiDAR with vision sensor such as it has been proposed in [34], where a three-dimensional camera has been jointly used with a LiDAR that was not able to detect obstacles over and under its scan field.

Several works focus indeed on the exploitation of vision processing to improve accuracy of vehicle localization. Simplest solutions propose to exploit cameras to detect the crop rows for helping the steering of the vehicle [28], [38]. However, main applications of vision sensors in the agriculture are related to classification considering colour, shape and size for two-dimensional images, while stereovision is typically used for three-dimensional analysis [33], [37]. Visual odometry has been also considered for integration in the navigation system of autonomous tractors [36]. However, it seems that it was tested only in orchard where trees can be used as points of reference for the computations.

A localization method, based on the Received Signal Strength Indication (RSSI) from the wireless access points dislocated around the agricultural fields, have been proposed for human operator localization. This method can be considered to be extended to autonomous agricultural vehicles. The wireless-based method has been developed to complement GNSS technology to improve its availability and reliability [40].

Exteroceptive sensors, both vision sensors and LiDAR or RADAR, have been used in some cases to implement SLAM approach [29]. SLAM has been proposed to complement GPS localization solution for the situations where dense foliage may block the GPS signal. Drawback of SLAM is the high computational cost required for building the map of the environment.

Several studies report the accuracy in the vehicle positioning that they have been able to achieve. Solutions are comprising odometry, inertial navigation and GPS (typically RTK-GPS) localization methods and, in some cases, these sensors are assisted by perceptive navigation approaches, either vision-based or LiDAR/RADAR-based. First aspect to highlight is the low-speed which all vehicles sustained. Autonomous tractors have been tested for speeds up to few m/s, i.e. in the range from 10 to 15 km/h maximum. However, the accuracy has always been very high. In most of the cases, the accuracy was below 5 cm [33], [37], [38], [39], [41].

5.2 Obstacle detection

In agricultural autonomous vehicles, the obstacle detection mainly relies on vision sensors, such as monocular camera, multispectral camera, thermo-camera (infrared) and stereoscopic camera, and on other perception sensors, namely LiDARs and RADARs, [34], [35], [43], [45].

Monocular cameras are typically used to detect upright humans, while depth sensors, such as LiDAR and stereovision cameras, are more effective to detect objects that protrude above the grounds. Both LiDAR and stereovision are typically jointly used since LiDAR performance is not significantly affected by weather and light conditions as visual cameras. Instead, stereovision provides the highest resolution improving object recognition. Thermal camera is instead useful to detect objects that have a distinct temperature with respect to the environment. This feature is important to recognize humans in any posture. Environment with higher temperature can however make thermal detection more difficult [43]. Omni-directional stereo vision has been also explored for human detection. The developed system was able to detect people in the range of 4 to 11 m [47].

In [34], LiDAR sensor has been complemented with a three-dimensional Time of Flight camera (equipped with a light source, typically infrared, to determine depth information of the environment) to overcome the limited scan field of the LiDAR.

Stereovision, LiDAR, RADAR and thermography perception sensors were also exploited in the Ambient Awareness for Autonomous Agricultural Vehicles (QUAD-AV) project [44]. New processing methods of sensors data have been proposed targeting the detection of obstacles and the classification of traversable ground surfaces. Different combinations of these sensors were considered in order to compensate weaknesses of each sensor. For example, vision sensors can solve issues related to sparseness of data and low acquisition frequency introduced by LiDAR sensor, while LiDAR can improve performance of the overall system in poor lighting conditions, shadows and lack of texture. The proposed perception system has been experimentally validated and it has been demonstrated that it was able to perform an accurate three-dimensional scene reconstruction from near range up to several metres away [44].

The RADAR used in the QUAD-AV project [44] is operating at 24 GHz band and it was introduced in [52]. Millimetre-waves RADARs are particularly suited for applications in outdoor environments since, thanks to the use of millimetre wavelengths, it is possible to gather a reliable and robust information also in degraded visual conditions, such as weather events or dust [52]. The robustness of millimetre-waves RADARs in critical environmental conditions were also confirmed in [53].

Many works focus their effort in providing also objects and ground classification. In [49] a system made by LiDAR and stereovision has been developed to detect traversable ground surfaces. Two self-learning classifiers, one based on LiDAR data and one based on stereo data, have been developed for a proper ground detection. A monocular colour camera, a RADAR, and a LiDAR have instead exploited in [50] for a global mapping approach. Classification algorithms have been introduced to associate sensors data to specific labels such as “human”, “vehicle” and “vegetation”. A similar classification approach has been targeted also in [51]. In this work, the fusion of two-dimensional camera images with three-dimensional data from a LiDAR has been exploited for an accurate perception of environment. Instead in [46], authors introduce a classification algorithm based on deep learning and stereo camera.

A collision avoidance algorithm for fleets of autonomous agricultural robots have been proposed in [28]. The proposed solution relies on a centralized control unit that, after receiving the position of each vehicle via wireless communication links, compute the future trajectories of the robots and identify possible conflicts.

5.3 Communication

The communication aspects have not been much explored in the research studies on autonomous driving in the agriculture. However, the exchange of information within each vehicle and among vehicles and the infrastructure is essential for the development of self-driving agricultural robots. Some details in different works have been provided.

5.3.1 Vehicle to infrastructure communication

Wireless communication links have been usually established between each autonomous tractor and a control center. Indeed, even if vehicles are supposed to be completely autonomous, a remote supervision or remote control options is usually possible exploiting wireless communication [28], [38]. In some specific works, basic fleet management strategies have been also proposed [28], [55].

Wireless communication are typically based on standardized wireless technologies, mainly related to the IEEE 802.11 family of standards and they are implemented using commercial wireless routers [39], [45], [55], potentially employing some special outdoor antennas [45]. Special-purpose UHF (Ultra High Frequency) narrow band modem has been also employed [54]. UHF narrow band communication permits to achieve more reliable communication for longer distances and at lower power with respect to WiFi-based communication systems.

5.3.2 Intra-vehicle communication

The communication network on the vehicle has the scope to interconnect the sensors, the control modules and the actuators. Most common communication system exploited are based on Controller Area Network (CAN) bus, Ethernet and RS-232 serial communication systems [28], [33], [39], [41], [43], [45].

Particular focus to intra-vehicle networking was in [42] where authors evaluate the potential of a CAN bus to be used as the communication network for a distributed control system on an autonomous agricultural vehicle.

5.4 Standard

The agricultural environment is highly unstructured and no specific manoeuvres have to be performed since operations of autonomous agricultural robots are typically performed on private fields. However, autonomous tractors have to respect specific safety measures to detect risks in real-time and to avoid people with high reliability.

The International Organization for Standardization (ISO) 18497 standard [48] addresses the human safety aspects for autonomous agricultural vehicles. The objective of this standard is to specify the requirements and to provide direction on autonomous agricultural operations.

The requirements specified by the ISO 18497 specify which is the minimum obstacle that must be detected with an accuracy of 99.99%. An olive green barrel shaped object resembling a small or seated human in green clothing has been defined as the minimum obstacle by the ISO 18497 and it is typically used as term of reference to evaluate the effectiveness of obstacle detection system [43].

5.5 Prototypes and product concepts

Several prototypes of autonomous tractors have been created in several research works. Most of them are typically traditional tractors that have been equipped with additional sensors and control modules. In the following of this Section, two prototypes, developed to demonstrate the effectiveness of the proposed autonomous agricultural solutions, are introduced as exemplary cases. Furthermore, the concept for an autonomous tractor from Case IH is introduced.

5.5.1 RHEA project

The RHEA project (Robot Fleets for Highly Effective Agriculture and Forestry Management) [56] is a European FP7 (Seventh Framework Programme) that was focused on the design, development, and testing of automatic robotic systems to be used for agricultural applications.

Figure 2 - (a) Original CNH Boomer-3050 tractor, (b) modified RHEA vehicle, (c) external equipment on-board the mobile units, and (d) internal equipment distribution inside the mobile unit's cabin [28].

In this project, a commercial vehicle was equipped with the required equipment to implement the RHEA autonomous driving solutions. The vehicle that was selected is a CNH Boomer-3050 [28]. The tractor's cabin has been modified to contain the computing equipment. Other equipment for the perception and localization systems were installed outside the cabin. In Figure 2, the RHEA vehicle is shown.

The complete list of the installed equipment contains a vision system for weed and crop row detection, a LiDAR (laser range finder) for obstacle detection, communication equipment for connecting with other mobile units and the control center, GPS system, an IMU, a vehicle control unit for the steering, braking and other driving tasks, a central controller that collects information from all sensors and computes the actions to be performed by the actuators, an additional energy power supply based on a fuel cell.

5.5.2 Hands Free Hectare project

The Hands Free Hectare project of the Harper Adams University and Precision Decisions had the objective to plant, tend and harvest a crop with only autonomous vehicles and drones [57]. An Iseki tractor (Figure 3) has been used as starting basis to create the autonomous driving tractor for the project. Small vehicle has been used since the project team believes that the use of smaller agricultural machines could improve soil and plant health. The project accomplished to demonstrate that a field can be farmed without human intervention.

Figure 3 – Modified Iseki tractor of the Hands Free Hectare project [57].

5.5.3 Case IH and CNH cab-less autonomous concept

A concept of an autonomous cab-less tractor has been proposed by Case IH and CNH [58]. Navigation is based on GPS signal. RADAR, LiDAR and on-board video cameras have been used to sense stationary or moving obstacles in its path. The vehicle moves on predefined trajectories or using remote supervision. In case of obstacle detection, tractor can behave autonomously, or it can ask for a remote decision from a human supervisor.

Figure 4 – Case IH autonomous concept vehicle [58].

6 Automatic Guided Vehicles in industrial environment

The Automatic Guided Vehicles (AGV) are currently widely employed in the industrial sector to implement flexible Material Handling Systems (MHS). AGVs are typically used for handling products, partially manufactured products or raw materials in warehouses or between different stations in a production line [59], [60].

The flexibility introduced by AGVs allows to overcome issues related to machine failures or to adapt the handling system to product changes due to seasonal and cyclic variations. To effectively achieve these benefits, AGVs should be easily configurable and adaptable to floor layout changes in order to avoid waste of time in the rearrangement of the workplace. They should also not rely on remote supervision for greater flexibility, achieving a significant autonomy in the navigation task. Furthermore, the AGV system should be effective for operations in structured or partially structured environments in order to ensure industrial grade accuracy, repeatability and reliability. Indeed, AGV are requested to perform precise manoeuvres, such as pick-up and delivery of material or products, in order to have an efficient manufacturing system [60], [63].

In the following of this Section, the main localization methods are introduced in Sec. 6.1, while obstacle detection strategies are described in Sec. 6.2. The communication aspects are presented in Sec. 6.3 and standards for AGVs are introduced in Sec. 6.4. AGVs developed for industrial use and also small AGVs developed for experimental purposes are considered in this survey. Research prototypes and commercial products are then detailed in Sec. 6.5.

6.1 Localization and navigation

The current commercial AGVs do not plane the route by themselves, but their navigation is based on predefined paths that they should follow [59]. The predefined routes are memorized in AGVs and the AGVs need just to select the most appropriate route when receiving a specific order [60].

The main difference is how the AGVs follow the predefined path, i.e. the navigation functionality. The approach to the navigation is strictly correlated to the flexibility that is required in the handling system. If frequent modifications to the layout of the manufacturing environment are performed, it would be better to opt for an easy-to-change navigation system [59], [63].

The localization and navigation approaches for AGVs can be associated to two main categories: i) *fixed path* and ii) *open path* methods [59]. In the fixed path approach there is a guide that indicates the precise path that the AGV should follow. The AGV is only required to have a sensor to detect the guide. This is basically a localization method based on a continuous artificial landmark. The AGV in the open path localization should have the freedom, in theory, to follow any path between two locations. In this case, the AGV requires to locate itself in the environment using a map or other methods that permit to the AGV to achieve a sufficiently precise localization.

6.1.1 Fixed path navigation

The first employed fixed path navigation method was based on a wire embedded in the floor. By inducing a frequency in the wire, the AGV, equipped with the required sensor, can detect and follow the wire. This approach is not suitable in the case that the layout of the environment changes frequently since modifications to the navigation systems of AGVs involve structural changes to the environment, i.e. remove the wire embedded in the floor and place a new one [59], [69].

Another approach for fixed path navigation is based on magnetic tape. In this case, changes can be performed easily since the magnetic tapes can be quickly removed and repositioned [59], [72]. However, the manufacturing system has to be stopped in any case since a physical change to the environment is required. Other proposal is to perform line navigation exploiting a colour visual sensor that detects a line guide positioned on the floor [76].

A more complex approach is presented in [64] where AGVs visual line-based guidance is enhanced by the exploitation of visual landmarks and RFID (Radio Frequency Identification) tags. Visible landmarks can provide additional navigation information about the guide-path and, in particular, about the intersections.

They can exploit different shapes or geometric dimension of lines to this scope. RFID tags instead can provide to the AGVs information about the global localization and the topological relations of crossroads.

6.1.2 Open path navigation

The three main localization methods, typically used in open path navigation, are based on artificial landmarks, dead reckoning and Cartesian guidance [59], [72]. In the following of this Section, an overview of these and of additional methods is provided.

The most common approach that AGVs employ for open path navigation is to exploit artificial landmarks. Reflective beacons (i.e. the artificial landmarks) are installed in the navigation environment and the AGVs typically use a laser-based sensor to detect the position of these beacons [75]. In the specific, the distance between the AGV and each beacon can be computed. The AGVs then determine their position exploiting the geometric information related to the identified beacons. Main issues of this approach are that it is necessary to prepare the environment (i.e. accurately position the reflective beacons) and that the localization is not robust to interferences due to obstructions of beacons and to significant layout changes. Further issues are related to light sensitiveness of the laser-sensors and their high cost [62].

Vision-based method is also proposed for AGV localization exploiting artificial landmarks. AGVs can use a camera to detect visual artificial landmarks that can provide information related to the positioning and the control of the AGVs [71]. Other approach is to exploit both artificial landmarks and natural geometrical landmarks that are registered in a first moment when creating the map of the environment [66]. Otherwise, relying only on natural landmarks is as well feasible [67]. The possibility to use just natural landmarks (i.e. landmarks that can be also man-made, but that are not installed for the navigation of the AGVs) can be an effective solution since it does not require to prepare and to maintain the environment for the AGVs' navigation.

An alternative option is to use an active beacons-based localization method. In [79], the localization is based on both artificial landmarks detected by a laser-based sensor and on active beacons sent by an IEEE 802.15.4a network. The AGV can perform range measurements based on Time of Flight techniques to determine the distance between itself and the nodes of the IEEE 802.15.4a network. The data from both approaches are fused together to improve the localization accuracy.

Dead reckoning is also widely used in open path navigation. Odometry and inertial navigation are the main dead reckoning methods exploited in AGVs navigation. However, the accuracy of dead reckoning approaches significantly decreases over time due to the cumulative errors. It is then required to recalibrate from time to time the position using some additional devices. Most common recalibration device is a magnet on the floor. This necessity limits the freedom of AGVs in choosing the path since the AGVs need to pass over the recalibration devices [59].

An open path navigation method based on dead reckoning is presented in [62]. In this work, magnetic nails are used to eliminate the error accumulated by the inertial navigation system. As the AGV passes over a magnetic nail, the navigation state of the vehicle is reinitialized using the information provided by the magnetic nail. This method is convenient with respect to magnetic tape since it is easier to be reconfigured in case of necessity.

Other re-localization method can be based on the visual processing of landmarks. Indeed, visual landmarks, such as barcodes, QR-codes or AR (Augmented Reality)-codes, can be used to provide additional information to the AGVs and not only be used as landmark. For example, in [69] several AR-codes are placed on the ground and they are recognized by AGVs using camera and a feature detection algorithm. In this case, the AR-codes provide information to uniquely identify them and restore the localization exploiting the measurements of different landmarks.

Another method based on visual processing for correcting dead reckoning errors is introduced in [72]. The method proposed is based on the characteristics of the floor texture in manufacturing plants and warehouses. The floors in these environments are typically characterized by the presence of several landmarks. This visual texture, which can be identified at the millimetre scale, is persistent and locally unique and it can be due to aesthetic or operational purposes, or also due to normal wear and tear. It is possible to track these features and create a navigation map. The AGVs can sense the floor using a camera and then match the acquired image with the map to recalibrate the dead reckoning navigation system.

The last method that is described is known as Cartesian guidance. This method exploits the characteristics of a Cartesian space. A fixed grid pattern is defined for the entire floor area and the AGVs exploit the grid to navigate the environment [59]. In particular, AGVs sense the floor to detect the lines of the grid and the intersections that have known Cartesian coordinates. The detection of the grid and of the intersections can be based on visual processing or on other techniques. For example, in [63] passive RFID tags are positioned at the intersections and the AGVs are equipped with RFID readers in order to detect these tags.

6.1.2.1 Maps

One important aspect of open path navigation is that the AGVs need a map or an alternative method to know their position in order to be able to navigate between the start and the destination of its path [59]. All approaches of open path navigation can be included in the following three main categories [68].

Map-based navigation

The AGVs have available maps of the environment. Maps can be either grid (geometric) map, where a precise representation of the environment is provided, or topological maps, where high-level information are only provided [59], [64]. For example, in a first level topological map, two rooms are presented by a node for each of them and an arc between these two nodes is present if there is a door connecting these two rooms [59].

Three-dimensional maps can be also exploited. For example, in [70], a LiDAR (or laser scanner) with 360° scanning ability is used to create a three-dimensional representation of the environment. Other approach to create a map is presented in [72], where, as previously described, a map containing the visual textures of the floor is created and used for navigation.

Map-building-based or Simultaneous Localization and Mapping (SLAM) navigation

In this case, the AGV itself builds a map or a representation of the environment that then it uses to navigate. The map can be realized using a camera to implement a visual SLAM [65] or exploiting laser scanner data (LiDAR) with odometry measurements to create a two dimensional occupancy grid map [77].

Map-less navigation

The AGVs do not resort on any representation of the environment in this approach. They just identify objects present in the environment and they use these objects as references. Based on the observed position of these reference objects, the AGVs generate motions accordingly.

Main issue of this approach is the perceptual aliasing that occurs in environments with periodical structures, e.g., a corridor where doors are equally spaced. In such specific environments, the appearance of the environment to the AGV can be the same in different locations making impossible to associate the current representation to a single reference one [61].

Typically, map-less navigation is implemented using vision sensors as in [61] and in [78]. In both works, the AGVs are equipped with an omnidirectional camera that is used to acquire images to be matched with reference images in order to determine the position of the AGV. The use of an omnidirectional camera is advantageous since it permits to directly identify the location with just a single image since it is not sensitive to direction in which the image has been acquired.

6.1.3 Fixed camera

Some works ([77] and [80]) also proposed to use fixed ceiling cameras to detect the positions of the AGVs. The ceiling cameras constantly monitor all AGVs and determine their position on a global map. Combining this information with on-board dead reckoning sensors, the AGVs are able to accurately determine their position. AGVs are required to be wirelessly connected with the fixed infrastructure to receive the positioning information measured by the fixed cameras.

6.2 Obstacle detection

The AGVs are typically equipped with sensors to detect potential obstacles. Both visual (camera) and non-visual (LiDAR, SONARs) sensors are employed [67]. No significant advances or new solutions are presented for what concerns obstacles detection. The use of available sensors and the integration of the gathered information from these sensors is typically performed.

For example, in [70] three LiDARs with 180° scanning ability are mounted on the AGVs, two at the front left/right sides and one at the rear side, ten ultrasonic sensors are positioned all around the AGV to detect obstacles in the near left/right sides. Three cameras are also used to detect moving objects. Other works rely on LiDARs ([72], [75]), ultrasonic sensors [74] for obstacle detection and avoidance.

The fixed ceiling cameras used for AGVs' localization can be also employed to detect and locate potential obstacles for each AGV. Information about possible collisions and dangers is then communicated from the centralized system to the AGVs [77], [80].

6.3 Communication

No particularly detailed information or specific advances in the communication for the AGVs is available. Sensors and modules on AGVs are typically interconnected using the CAN bus [59], [75]. Wireless communication is in some cases also implemented on the AGVs to allow exchange of information between each AGV and the centralized control system. Wireless communications are mainly based on IEEE 802.11 standards ([59], [75]), but other communication standards are also explored, as for example standard IEEE 802.15.4a in [79].

6.4 Standards for AGVs

The international standards organization American Society for Testing and Materials (ASTM) International devoted the Committee F45 to Driverless Automatic Guided Industrial Vehicles. The scope of this committee is to develop standardized nomenclature and definitions of terms, recommended practices, guides, test methods, specifications, and performance standards for driverless automatic guided industrial vehicles [73].

Subcommittees have been organized to tackle specific aspects of the AGVs standardization. Among these aspects, it is possible to find docking manoeuvres and navigation approaches, objects detection and communication issues. Standards are mainly related to define the terminology, the minimum safety requirements and test procedures.

6.5 Prototypes and commercial products

Most advanced prototype solutions are based on commercial forklifts or tugs that are modified to be equipped with additional sensors, control and communication devices [59], [60], [70], [72].

In Figure 5 the commercial vehicles exploited in [72] are shown. In the bottom left of the picture the tug (or tractor) is presented. This AGV is equipped with a single downward-looking camera to detect landmarks on the floor. Instead, the forklift on the right side has two stacking cameras mounted to the roll bars and a forward-looking camera which moves with the forks. Wheel encoder is also mounted, as well as string encoders to be used to measure motions of the mast. The forklift is usually equipped also with two LiDARs that are not present in the picture.

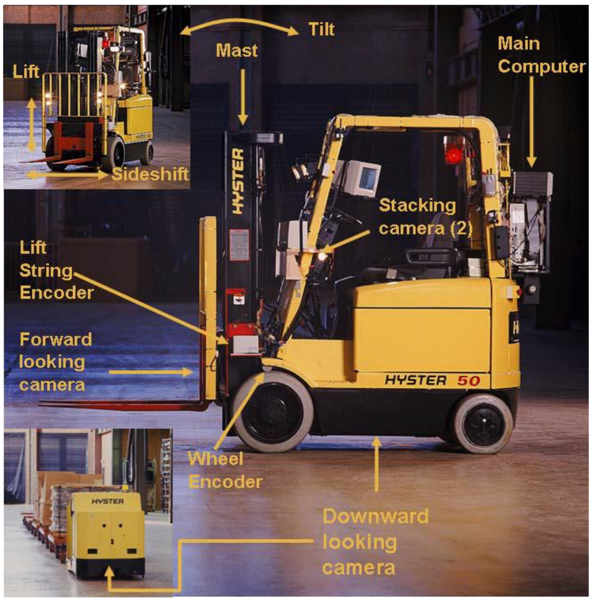


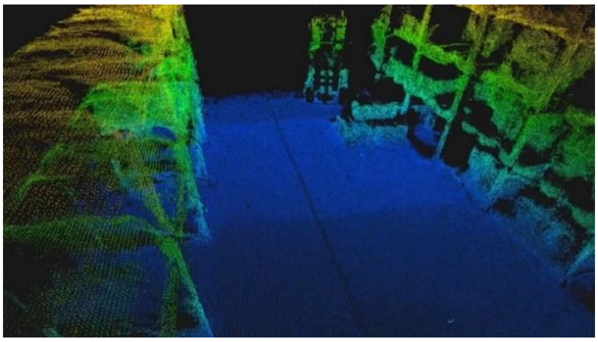
Figure 5 – Tug and forklift used for experimental purposed in [72].

Several commercial solutions can be already found in the market. They mainly differ for the destination of use of the AGVs and on the type of navigation and related sensors employed.

CANVAS Visual Perception [81] offers AGVs that are equipped with multiple pairs of stereo cameras and LiDARS. The AGVs, which is introduced in Figure 6(a), is able to detect and recognize objects, signs, markings and gesture by people. The AGV can detect if it is indoors or outdoors and with or without GPS. Stereo cameras are used to create a complete three-dimensional representation of the environment, shown in Figure 6(b), for safety issues. LiDARs are mainly exploited to detect obstacles.

AGVs proposed by Savant Automation [82], namely Automatic Guided Carts, are shown in Figure 7(a). They are based on open path navigation relying only on inertial navigation. The navigation of the AGVs is then achieved employing only a solid state inertial sensor to compare the heading and position of the AGV to a CAD route map in the vehicle's memory. Instead, the SmartCart Automatic Guided Carts by Motion Controls Robotics [83], shown in Figure 7(b), have the navigation system based on magnetic tape guidance.

(a)



(b)

Figure 6 – (a) CANVAS AGV and three-dimensional representation created by the AGV [81].

Mobile Industrial Robots (MiR) [84] has introduced different version of AGVs. These are mainly based on LiDAR and three-dimensional cameras that are used by the AGV to sense the environment. Navigation of the AGV is based on prebuilt maps and on the available perception sensors. The AGVs are provided with standard Wi-Fi or Bluetooth communications for control purposed. The MiR200 AGV is shown in Figure 8, where most relevant perception sensors are detailed [85].

(a)

(b)

Figure 7 – Automatic Guided Cart of Savant Automation [82], (b) SmartCart Automatic Guided Carts by Motion Controls Robotics [83].

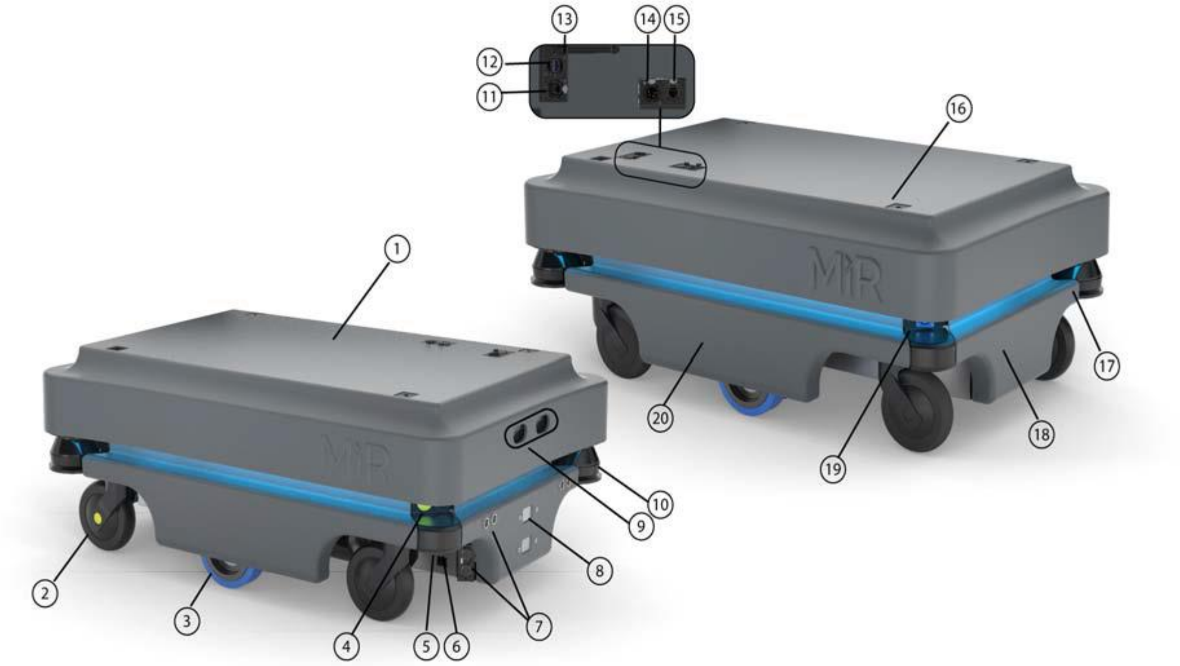


Figure 8 – MiR200, in details (7) ultrasonic sensors, (9) 3D depth camera, (10) front LiDAR, (17) rear LiDAR [85].

7 Autonomous vessels for unmanned maritime transportation

Autonomous vehicles in the maritime environment are either Autonomous Surface Vehicle (ASV) or Autonomous Underwater Vehicle (AUV). These vehicles provide support to surveying, mapping and monitoring applications that can be related to climate, environmental, scientific, commercial or military aspects [86], [87], [94].

Autonomous maritime vehicles are usually characterized by small size, high flexibility and mobility, low prices and low operational costs, high precision and extended range. These characteristics are essential for their application target. Indeed, ASVs and AUVs are usually employed to perform tasks in challenging environments that may not be suited for manned operations. Long-lasting or long-range surveillance missions may not be feasible to be performed by humans. Other limitations for manned operations are the environmental conditions, such as extreme cold or hot temperature, in which the task should be performed. Furthermore, safety reasons in case of military tasks is another motivation to employ unmanned AUVs [87].

The structure and the elements of an ASV or of an AUV are strictly dependent on the mission that the vehicle has to carry out. However, it is possible to identify the following basic items that each autonomous maritime vehicle has to include: the hull and auxiliary structural elements, the propulsion and power system, the guidance, navigation and control system, the communication systems, sensors equipment, the ground station [86].

The following sections are focused on some specific aspects characterizing the maritime navigation and on the main technological solutions about sensors and communication aspects. In details, the main regulations of maritime transportation are introduced in Sec. 7.1 and in Sec. 7.2. Localization approaches are presented in Sec. 7.3, while obstacle detection methods are explained in Sec. 7.4. Overview of the communication technologies used in maritime transportation is provided in Sec. 7.5. Standards for autonomous vessels are introduced in Sec. 7.6. Prototypes, commercial products and advanced autonomous ships concepts are presented in Sec. 7.7.

7.1 International Regulations for Preventing Collisions at Sea (COLREGs)

One main aspect, which is targeted when developing autonomous maritime vehicles, is the interaction with other manned or unmanned vessels. When the ASVs and the AUVs operate in regions where other ships are present, they need to safely navigate avoiding collisions.

Autonomous vessels are required to respect the *Convention on the International Regulations for Preventing Collisions at Sea* (COLREGs), also known as “Rules of the Road”. This Convention has been adopted in 1972 by the International Maritime Organisation (IMO) [88] and it consists of a set of guidelines that defines the procedures for collision avoidance and determination of the right of way.

In the COLREGs, potential collision scenarios, such as overtaking, head-on situation and crossing, are described and suggestions about the possible manoeuvres to avoid the collision are provided. However, these guidelines were conceived for manned ships and they are subjective, leading to possible different interpretations and, consequently, to misunderstanding errors [89].

7.2 Automatic Identification System (AIS)

A recent new requirement of the maritime transportation system is that ships must be equipped with specific transponders to automatically transmit data about the identity and the status of the ship (position, heading, destination …) to other ships or to the coastal authorities. These transponders are named as Automatic Identification System (AIS) [90].

This requirement has been introduced in the 2000 by the IMO in a new version of the Chapter V, which is about the navigational equipment that ships need to carry on-board, of the International Convention for the Safety of Life At Sea (SOLAS). The regulation specifies which ships, based on tonnage and engagement, must have the AIS, however this system is becoming more and more widespread. Indeed, as it is detailed in the following Sections, data from AIS can be exploited to complement information from sensors for both localization and obstacle detection [87], [89].

7.3 Localization

The localization of ASVs is typically based on the integration of the information from the GPS, or similar satellite positioning systems, and from IMUs [86], [87]. The AUVs can hardly rely on GPS technology since they mainly operate underwater where the GPS signal is not available. The AUVs usually exploit inertial sensors, such as gyroscopes and accelerometers, pressure sensors for measuring the depth, Doppler Velocity Log or cameras [91].

Some ASVs utilize Differential GPS (DGPS) to achieve a more accurate positioning. The DGPS, as introduced in Sec. 5.1, is an advanced GPS system that relies on differential measurements performed between the GPS receiver on-board the vehicle and a second fixed receiver positioned in a known point. These systems are typically more expensive than traditional ones and they can be employed in area covered by the fixed second receiver. A DGPS, implemented together with an inertial navigation system, achieved an accuracy in the range of 1 to 10 m [89]. Other system, always based on inertial navigation and DGPS, presented a typical accuracy of 3-5 m [92].

The navigation systems based on GPS and IMU are characterized by imprecisions in the position estimated due to environmental noises, accumulative errors resulting from inherent drift, time-varying model uncertainties and also to sensor faults [86]. Several research works focus on which corrections may be performed to enhance the accuracy of these systems. As example, in [95] authors proposed to include in the navigation system, based on GPS and IMU, a high-accuracy, multi-rate inertial integration algorithm to compensate the non-idealities of the inertial sensors.

An alternative option is to equip the vehicle with additional sensors that can be exploited to correct position drifts. In [103], the navigation system is composed by an IMU, a compass, a Doppler Velocity Log, a GPS and wind sensor. Furthermore, active sensors, such as RADAR, LiDAR, SONAR, vision sensors or cooperative positioning methods are other approaches to estimate the position of the vehicle or to increase its positioning accuracy. These approaches are introduced in the next subsections.

7.3.1 Simultaneous Localization and Mapping (SLAM)

Active sensors and cameras are mostly exploited for maritime localization integrating SLAM system with the common GPS and IMU navigation system. Some examples are introduced hereafter.

In [91], a SLAM system, based on stereo vision cameras, is integrated with information provided by a Doppler Velocity Log, a pressure sensor, a GPS and an IMU. The SLAM is able to improve the position accuracy thanks to the additional pose constraints obtained by the stereovision sensors.

A SLAM approach based on the mapping of above and below the water surface is proposed in [93]. The sensors for mapping are LiDARs and a low-cost webcam for mapping above the surface, while for the underwater mapping imaging SONAR is employed. LiDARs are positioned in such a way that a three-dimensional reconstruction of the environment is possible. SLAM system complements the data from IMU, GPS, Doppler Velocity Log and three-axis magnetic compass.

SLAM strategy introduced [105] is further enhanced with features extraction from the acquired images. Indeed, the identification of landmarks, already identified in previous observations, can improve the efficiency of the SLAM.

The navigation of the AUV in [106] differentiates instead the case that the environment is known and a map is available from the case in which no information about the environment is available. In the first case, a SONAR is employed to create a local map to be matched with the global one. In the latter case, the proposed SLAM method is beacon-based, i.e. acoustic transponders with unknown position, since it is assumed that the environment does not offer significant features to be recognized. The transponders transmit only range information that is used to jointly position the vehicle and the beacons.

7.3.2 Cooperative positioning

A Cooperative Vessels Positioning approach can be also employed in the maritime transportation sector to further increase the accuracy of GPS or to complement it in case of degraded operating conditions.

Cooperativeness among ASVs is indeed a widely explored solution not only limited to positioning, but also to several other navigation aspects [86].

A proposal for Cooperative Vessels Positioning is introduced in [107]. In that work, several positioning methods are explored considering the availability of range measurements among the vessels achieved using Time of Flight ranging techniques or RADARs.

7.4 Obstacle detection

The ASVs and the AUVs are required to efficiently detect obstacles to navigate in a real-world environment. Other ships and maritime vehicles need to be timely identified in order to perform manoeuvres compliant to COLREGs. Sensors can be divided in two main group: active and passive (vision) sensors. Cooperative obstacle detection has been also considered.

Typically, several different sensors are jointly used since they present different perception features and also they experience a different impact from weather and environmental conditions, such as winds, waves, currents, sea fog and water reflection [86].

Other aspect to consider in the obstacle detection is the vehicle' speed. Typically, limited speeds are considered during experimentation. However, some works specifically target this aspect. For example, in [94] an obstacle detection system has been developed and tested at high speeds cases [94].

7.4.1 Active sensors for maritime obstacle detection

The active sensors for obstacle detection, which are mainly exploited for autonomous maritime vehicles, are RADAR, LiDAR and SONAR.

The RADAR is the sensor that is typically used for obstacle detection in the far-field [86]. Marine RADARs have usually operating ranges from 1 to 12 km [87]. Limitations of RADARs is the mechanical scanning rate and the difficulty in identifying close objects, i.e. less than 100 m. Some specific type of RADARs, namely the Ka-band RADARs, can be more effective at short ranges, but they have a limited far range resulting in an operative range from 30 m up to around 3 km [92].

RADARs are typically provided with an Automatic Radar Plotting Aid (ARPA) that is used to better visualize RADAR's perceived data and to provide also a classification of identified obstacles. Indeed, ARPA is usually integrated with the AIS to further improve the classification of the identified objects [89].

LiDAR is mainly used as complementary sensor to RADAR since LiDAR effectively detect objects in the short field, i.e. up to 100 m [87]. In details, LiDAR can be used between 8 and 120 m. One feature of the LiDAR is that the wavelength used by the lasers is not suitable for having the radiated energy well reflected by the water's surface. This feature makes the LiDAR very effective for detecting objects. According to [87], tests performed using LiDAR show that it can well identify objects such as buoys and boats even at very short distances. Issues of LiDAR is again the mechanical scanning rate, as for the RADAR, and the scarce detection of small objects at long distances due to the relatively low angular resolution [92]. Some performance of LiDAR in the maritime environment are presented in [102] where the employed LiDAR was able to detect a target of one meter in length from a distance of 100 meters with a typical range measurement accuracy lower than 10 cm.

The SONAR is mainly employed for detecting obstacles in underwater environments [86]. SONARs can detect both moving and fixed objects at different ranges [104]. Advantage of SONAR is that is not affected by any visual restrictions, while a disadvantage is due to the echoes received from surfaces or other similar devices. This causes poor resolution and low accuracy. Thus, the millimetre-wave is typically used in SONARs to achieve a fine resolution for target detection at short ranges and also not moving objects for stationary target detection [104].

7.4.2 Vision sensors for maritime obstacle detection

Several vision sensors have been employed so far for object detection applications on the ASVs. Most common vision sensors are monocular camera, stereovision camera and infrared camera [86], [87].

Monocular camera has excellent angular resolution and there is no issues about mechanical scanning as for RADARs and LiDARS. Main issue of monocular camera is the reliability and the effectiveness of image processing algorithms to identify and characterize the different types of obstacles in all lighting conditions. Other issues are the poor range resolution and the need to find the horizon line in the image exploiting either visual methods or an inertial approach [92], [99].
Stereo camera are typically used to perform near-field obstacle detection [87]. Advantages of stereovision system are the excellent angular resolution and no need for mechanical stabilization. Main drawback is the limited range resolution [92]. Infrared cameras are instead suitable for low light conditions.

7.4.3 Cooperative obstacle detection

As already mentioned, cooperativeness among vessels has been widely explored, also for cooperative sensing and obstacle detection [86]. For example, in [96] the obstacle detection system exploit the AIS information received from other vessels.

7.5 Communications

Communications on ASVs and AUVs concern aspects related to wireless communications with ground control stations and other vehicles and also wired or wireless communications among on-board sensors and control modules [86]. On-board wired communications are typically based on CAN bus or Ethernet network [87]. Wireless communications are typically implemented using VHF links for ship-to-ship communications, while satellite communications are usually employed for ship to shore communications [97]. In the following of this section, main communication solutions are introduced. These solutions are not limited to ASVs and AUVs, but they can apply to all ships.

Inmarsat and Iridium are examples of satellite communications services. Inmarsat is part of the Global Maritime Distress and Safety System (GMDSS). Inmarsat operates in the L-band (1–2 GHz) offering a bandwidth of up to 432 kbps. Iridium is considered to be the only worldwide connectivity provider since the service is based on a large network of low earth orbit satellites. The service provided by Iridium in the L-band offers up to 134 kbps bidirectional connectivity. Services based on Very Small Aperture Terminal (VSAT) systems are also available. For example, a global C-band (4-8 GHz) service achieving 4 Mbps is offered by Intelsat [98].

The international legislation requests that other mandatory communication systems are installed on-board of the ship. In addition to AIS, which has been already mentioned before, the most important communication systems that ships must have are VHF radios with Digital Selective Call (DSC) functionality and Emergency Position Indication Radio Beacon (EPIRB) equipment for emergency communication to other ships, airplanes and the COSPAS/SARSAT system of satellites [98].

7.6 Standards for unmanned maritime vehicle systems

The Committee F41 of the international standards organization ASTM International is dedicated to Unmanned Maritime Vehicle Systems. The scope of this committee is the development of standards and guidance materials for ASVs and AUVs in order to achieve and guarantee interoperability and modularity among the solutions. Standards are related, among the others, to aspects concerning autonomy and control, communications and maritime regulations [100].

7.7 Prototypes, commercial products and concepts

A wide development of ASVs and AUVs has been performed by universities and research projects over the years. We refer to [86] and [101] for a detailed survey of most important solutions. In the following of this section, two examples of research ASV and AUV platforms are provided.

In [96], the ASV, shown in Figure 9, is employed. The ASV is based on the hull of a SCOUT robotic kayak and it has been equipped with additional sensors to extend its perception capabilities. An integrated IMU and GPS sensor has been used for localization purposes together with a Doppler Velocity Logger (DVL) that is used to estimate the velocity through the water. The perception sensors include three scanning LiDARs, two of which are installed to scan vertically allowing a three-dimensional reconstruction of the environment, a low-cost webcam, two 30 m range LiDARs and an imaging SONAR for underwater sensing with a range of 10 m and a field-of-view of 45 degree. Two motherboards carrying a quad-core 2.83 GHz CPU and a low-power dual-core 1.6 GHz CPU have been installed for processing purposes [96].

Figure 9 – ASV based on SCOUT robotic kayak with additional sensors employed in [96].

The AUV of [91], named SPARUS II, is 1.6 m torpedo designed to operate up to 200 meters deep (Figure 10). The SPARUS II AUV is equipped with the following navigation sensors: a GPS, a pressure sensor, a Doppler Velocity Log and an IMU. A stereo camera and a laser-based sensor are also included in the equipment. The AUV is provided with Ethernet and WiFi interfaces for external communications [91].

Figure 10 – SPARUS II AUV [91].

Large availability of commercial ASVs and AUVs is present on the market. These vehicles are typically employed to perform different monitoring and surveying tasks. These commercial solutions can operate in remote control mode, semi-autonomously or fully autonomously thanks to auto pilot modules. SONARs, GPS systems, cameras are the most common sensors employed. However, it is not clearly specified which of these sensors are used for the autonomous driving. We mention as examples Seafloor Systems, Inc [108] and ASV Global [109] as ASVs that both offer ASVs products achieving a full driving autonomy. In Figure 11(a), the EchoBoat-ASV from Seafloor Systems is shown, while C-Worker 8 by ASV Global is shown in Figure 11(b).

(a)

(b)

Figure 11 – (a) EchoBoat-ASV by Seafloor Systems [108], (b) C-Worker 8 by ASV Global [109].

Advanced concepts for autonomous ships are also explored in several projects and by different enterprises. We mention, among the others, the MUNIN (Maritime Unmanned Navigation through Intelligence in Networks) project [110], the ReVolt ship concept by DNV GL [111], the OneSea autonomous maritime ecosystem concept by DIMECC [112] and the Ship intelligent vision by Rolls-Royce [113].

Common target of all the referenced initiatives is the development of autonomous ships to be devoted to freight transportations rather than small size ASVs and AUVs. In particular, One Sea Ecosystem and the Ship intelligent concept by Rolls-Royce envision a completely autonomous maritime environment to achieve benefit from safety, economic and environmental points of view.

8 Autonomous aerial vehicles

In this chapter, automatic driving technologies for Unmanned Aerial Vehicles (UAVs), considering both fixed-wing and rotary-wing UAVs, are explored.

Similarly to the case of autonomous maritime vehicles, UAVs are conceived to be employed in harsh environment and in dangerous situations for operations that can be critical for the safeness of pilots in case that manned aircraft are used. The main objective of UAVs is indeed to avoid the exposure of human people to critical situations that can be harmful for the pilot and other people on-board of the aircraft. Several other advantages can be obtained by removing human presence. For example, time duration of the mission is not anymore constrained to the physical needs of the human crew, such as the pilot fatigue. Other advantage of UAVs is the limited cost of some basic UAVs platform that permits their use for cost-sensitive applications that would not otherwise be able to use manned aircraft. UAVs are thus employed for all these civilian applications that are typically defined as dull, dirty and dangerous. One aspect that requires attention is the feasibility of UAVs to accomplish specific applications. Indeed, main issue of small and medium size UAVs is the limitation on on-board sensors and on the payload. We refer to [114], [115], [117] and [122] for more detailed description of all the introduced aspects.

A major issue of UAVs is the regulations for operating UAVs in outdoor environment. Concerning indoor operations, no rules and regulations are present since indoor flights are not considered as aviation. Instead, outdoor operations are strictly regulated by the appointed regulatory bodies [114]. Indeed, outdoor flights are required to operate in a legal and safely way. These regulations are not be expected to be modified to accept UAVs, but the latter are supposed to be compliant with existing regulation framework in order to operate at an equivalent level of safety with respect to manned aircraft [114]. Several critical issues, concerning the regulatory aspects, must then be solved for achieving a full exploitation of UAVs in every-day applications.

The rest of this chapter is organized as follows: in Sec. 8.1 the UAVs' localization methods most commonly employed are introduced. The obstacle detection practices are presented in Sec. 8.2. Communication solutions are described in Sec. 8.3. Standard related to UAVs' operations are mentioned in Sec. 8.4, while prototypes and commercial UAVs are introduced in Sec. 8.5.

8.1 Localization

The localization of UAVs, as in several other application fields, mainly relies on the fusion of IMU and GPS data [115], [116], [122]. Altimeter sensor, either barometric, LiDAR or RADAR, is also typically used to provide the height estimation and enhancing the positioning accuracy [122].

Other sensors that are used to estimate the navigation state of the UAVs are either active ranging sensors (SONARs, LiDARs, RADARs) or vision sensors [122]. Localization is typically achieved exploiting map-matching methods or using SLAM approaches. LiDAR and vision sensors are the most employed for both methods. Ultrasonic and infrared sensors are instead used to estimate the altitude of the UAVs. Their use is typically restricted to indoor flights or to ground detection during automatic landing. RADARs are scarcely used since they are high power consuming and too heavy for most of the available UAVs [115], [122], [135]. Low-weight RADARs, around 400 g, are also available and they are used typically as altimeter. However, they have a limited range of about 700 m and they are relatively expensive [122].

SLAM methods based on LiDAR can be effective for UAVs' navigation, but they present some critical limitations [115], [122]. Similarly to the case of RADARs, LiDARs consume more energy and they are heavier than visual sensors. Furthermore, UAVs typically flight in large unstructured environments where it is likely that a small number of features is present making more difficult the relative estimate of the localization. For all these reasons, vision sensors are usually preferred to be employed in UAVs' localization and mapping applications. Several different SLAM approaches exploiting cameras have been indeed proposed. Main difference is the type of camera, e.g. monocular cameras, stereovision cameras, omnidirectional or multiple cameras [115], [123], [136].

Advantages of cameras with respect to active sensors are that they are lightweight and not energy consuming. Main drawbacks of cameras are instead their sensitiveness to the lights conditions and the need of significant computational resources to execute, if possible in real-time, the image processing algorithms

[115], [122], [125]. However, to ease the computational requirements of these algorithms, vision-based localization methods are typically used jointly with IMU since the latter can predict the camera motion from frame to frame resolving scale ambiguity [116].

Another localization method widely employed on UAVs is visual odometry which is based on the analysis of consecutive frames to identify the relative motion of the vehicle with respect to specific features or landmarks observed in the images. Visual odometry system can be based on stereo [124], monocular [116] or omnidirectional vision sensors [122], [123]. Visual odometry can be exploited together with GPS and inertial state estimation. When GPS is available, the UAV can identify landmarks and determine where they are located in the map. If enough landmarks have been identified, visual odometry can be effectively used to determine the location of the UAV when GPS signal is absent or degraded [126]. Depth RGB cameras, that provide both images and depth information of the environment, have been also used for visual odometry and three-dimensional reconstruction of the environment in indoor operations [128], [139].

Some works also proposed to perform UAVs localization using ground-placed cameras that can estimate position and attitude of the UAVs. This method is not feasible in real-world applications due to practical limitations and it has been mainly employed for experimental testbeds [122].

Specific localization task of UAVs concerns the landing operation. Before landing, the UAVs need to identify suitable landing zones. Typically, an artificial landmark indicates the predefined landing area. Different image processing techniques have been proposed to effectively identify the landmark of the landing area [127], [130], [131], [138].

8.2 Obstacle detection

The obstacle detection functionality, known as Sense And Avoid (SAA) system in the avionic sector, is a critical issue that must be solved before that UAVs can freely operate in commercial air spaces [114]. Up to now it seems that commercial UAVs are seldom equipped with a SAA system. In this section, a review of the main sensors for SAA are provided considering also collision avoidance systems that are in use in traditional manned aircraft and that are suitable to be employed also on the UAVs.

Sensors for SAA can be divided in two main categories: non-cooperative sensors and cooperative sensors. The first comprises all those sensors that do not require any two-way communication, while the latter relies on two-way transmissions among aircraft and between aircraft and ground station. Several sensors from both categories are required to achieve a robust SAA system since cooperative sensors cannot detect all those obstacles, e.g. other aircraft or birds, that not broadcast their position information. An appropriate choice of the sensors is strictly correlated with the type of UAV, its feasible payload and its application [114], [117], [120], [122].

8.2.1 Non-cooperative sensors

Active (RADAR, LiDAR, Infrared sensors) and passive (vision sensors) non-cooperative sensors are both employed in SAA system. Main difference between these two sensors' categories is that active sensors illuminate the environment and sense the reflected signals to detect obstacles, while passive sensors just exploit the signals received from the environment, i.e. the natural reflected light.

Traditional sensor for obstacle detection on aircraft is the RADAR. However, it is not very suited to employment in the UAV' sector since it is heavy, expensive and energy-consuming for small and medium UAVs. New RADARs, which can overcome these issues, have been proposed, but achievable detection ranges are reduced to few hundred meters. Furthermore, they cannot provide the same level of details in imaging than vision sensors can instead provide [114], [120], [121], [133]. Synthetic Aperture Radar [129], active Doppler RADAR [137] and millimetre-wave RADAR [117].

LiDAR is often used since it can detect a wide range of targets, such as wires, extended and point objects, in a different geometric and weather conditions. According to the type of LiDAR employed, the detection range is from 200 m to 3 km. Advantage of LiDAR is its capability to detect non-perpendicular surfaces at high resolution. Main drawback is the limited field of view [121], [129], [134].

Other active sensor is based on infrared light. Infrared sensors can detect objects using reflected infrared light achieving a more realistic representation [129].

Passive sensors, i.e. visual cameras, have characteristics, such as small dimension, low cost and low power, that are more suited for the needs of UAVs. However, performance of cameras can be affected by specific weather and environmental conditions, e.g., fog, dust. Furthermore, cameras are characterized by limited ranges and they do not directly provide size or distance of the identified obstacle [114], [120], [121]. In addition to visible light cameras, infrared cameras can be also employed to detect obstacles exploiting infrared radiation [129].

Cameras can also be used to complement RADAR sensor. In [132], the sensors equipment for the SAA comprises a RADAR and four cameras, two working on visible light and two on infrared light. Cameras are employed to improve the tracking accuracy of the obstacles and to increase the information acquisition rate [132].

8.2.2 Cooperative sensors

Different cooperative system for collision avoidance among aircraft have been introduced. Main cooperative systems used are Traffic Collision Avoidance System (TCAS) and Automatic Dependent Surveillance – Broadcast (ADS-B).

TCAS is widely deployed in manned aircraft and it has to be compulsory installed according to the regulations of several civil aviation authorities. TCAS operates by interrogating the transponders of other aircraft to determine information about range, bearing and relative altitude. In particular, the range is computed using Time of Flight ranging technique, while bearing or azimuth are computed using a directional antenna that measures the angle of the signal received by the other aircraft. Additional feature of TCAS is the advices that the system provides to pilot for manoeuvres to be executed for collision avoidance. TCAS requires that all aircraft are equipped with transponders, otherwise they cannot be detected. Application of TCAS in small UAVs can be an issue since these UAVs have typical limited payload capabilities. Further issue about application of TCAS in UAVs is the need of certification whose process is complex and requires detailed test and analysis activities [118], [120], [121].

ADS-B broadcasts the identification, position, velocity, and intent of the aircraft to a universal access transceiver. The ADS-B system exploits an integrated GPS to know the position of the aircraft. Main advantages of ADS-B are the reliable communication technology used and the accurateness of the information broadcasted [120], [121].

8.3 Communication

No significant effort has been devoted to the communication topic among the activities related to autonomous UAVs development. Some small size UAVs are equipped with IEEE 802.11 standard-based interfaces, such as in [127].

It is expected, however, that UAVs will also be able to exploit satellite communications thanks to the increase of commercial satellite services. Additionally, it is expected that some UAVs will be employed as relay platforms for satisfying communication needs of other UAVs [129]. The latter aspect is well covered in [119] where an extended analysis of possible UAVs communication architectures is presented. The two main proposals are to have a centralized communication architecture or a decentralized one. In the first, a central node, for example a ground station, is present and all UAVs are connected to this and all transmissions go through the central node. In the latter, each pair of UAVs can directly communicate.

Other solutions for UAVs communication are those based on already existing communication systems in the avionic sector, such as the previously introduced TCAS and ADS-B systems.

8.4 Standards for UAVs operation

UAVs are required to comply with all civil aviation standards for operating within civil aviation space. However, national agencies have often set specific rules restricting the UAVs operation, even if remotely controlled [140]. To address this regulation fragmentation, international agencies, such as the International

Civil Aviation Organization [141] and the European Aviation Safety Agency [142], have currently on-going activities to uniform the UAV regulations to create a harmonized regulatory framework.

8.5 Prototypes and products

Several prototypes have been developed during UAVs related research activities. We refer to [122] for a detailed analysis of developed prototypes and related research innovations and achievements.

UAVs commercial products are available. Some autonomous functionalities are also provided, mainly based on GPS and inertial navigation. An example, shown in Figure 12(a), is the AscTec Firefly by Ascending Technologies [143]. Some autopilot modules are also commercially available for “plug and fly” application, such as Veronte Autopilot by Embention [144], shown in Figure 12(b). This product offers the compatibility with different aerial platforms. It includes GPS and several inertial sensors and it supports several sensors, such as magnetometer, LiDAR and RADAR. It offers full autonomous flight operations. Information about sensors exploited by the autopilot module are not publicly available.

(a) **(b)**

Figure 12 – (a) AscTec Firefly by Ascending Technologies [143], (b) Veronte Autopilot by Embention [144].

9 Autonomous driving cars

Fully autonomous driving cars, or self-driving cars, are a very challenging target that is being pursued by several research projects. Most known projects are carried on by high technology enterprises related to the Information and Communication Technology (ICT) domain and to the automotive sector. Tesla, Google-Waymo, BMW-Intel, Mercedes and Uber are some of them, just to mention a few. Effort is not only devoted to achieve self-driving cars, but also autonomous trucks or buses are currently being developed. CNH Industrial proposed for example the Z TRUCK IVECO concept that offers autonomous driving capabilities [153]. Increase the safety and the operational efficiency of the transportation system are among the main motivations for pursuing the development of autonomous cars [154].

The road environment, where autonomous driving cars circulate, implies to accurately solve several specific issues. Roads constitute indeed a structured environment, very crowded, characterized by many degrees of freedom, where only manoeuvres allowed by the regulations can be performed. Road signs and markings are used to specify the manoeuvres that can be performed, and self-driving cars are thus required to detect and understand them. Moreover, autonomous driving cars are expected to share roads with other road users, both other non-autonomous cars and vulnerable road users, such as pedestrians and bicycles. It is extremely important to ensure that autonomous cars are safe for their passengers and also to all other road users. Regulations for self-driving cars and liability in case of self-driving car accident are two fundamental aspects that need to be addressed before that self-driving cars can be used in the real world.

In the following of this chapter, the concept of cooperativeness in the vehicular environment is explained in Sec. 9.1. Main technological solutions for localization and obstacle detection proposed for autonomous driving cars are overviewed respectively in Sec. 9.2 and in Sec. 9.3.Communication and standard aspects are introduced in Sec. 9.4 and in Sec. 9.5 , while prototypes and concepts of self-driving cars are presented in Sec. 9.6.

9.1 Cooperative Intelligent Transport System

Autonomous driving cars are expected to leverage significant advantages by the Intelligent Transport System (ITS) [174]. The ITS is an application framework where innovative technological solutions, related to the overall transport system, are implemented for an improved management and a safer and more efficient use of the transportation system.

The development of ICT technologies, in particular of communication among vehicles and between each vehicle and the road-side infrastructure, enabled the definition of ITS solutions that, exploiting the communications, aim to increase travel safety, reduce the impact over the environment and improve traffic management [156].

Main focus of the recent ITS-related research is on cooperative-ITS aspects that comprise all those solutions in which actors of the ITS exchanged messages to increase safety and operational performance. Messages can be related to the status of the vehicle, e.g. speed, direction, position, or they can notify some specific action or alert [155], [167]. Cooperative vehicle positioning and cooperative collision avoidance are two applications of cooperative-ITS. Effectiveness of cooperative-ITS is however strictly related to the number of vehicles equipped with communication devices. Larger is the number of connected cars, greater is the effectiveness and the resulting advantages.

Other advantages of vehicle cooperative systems are a more effective management of traffic flows for a reduction of traffic congestion and of environmental impact. Further advantages are related to the safety and to the enforcement of the regulations such as speed limits and traffic lights [167]. Dynamic cooperative manoeuvres for platoons of autonomous vehicles can be also targeted [179].

9.2 Localization

9.2.1 GPS localization and related issues

The most common and widely used localization system employed in autonomous driving cars is the GPS localization system. However, the accuracy provided by GPS can vary significantly due to the low number of visible satellites, or for their geometric disposition or for other conditions that can affect the quality of GPS signals, such as blockage and multipath propagation issues [148]. In urban environments, a criticality is related to the presence of high buildings that significantly reduce the sky visibility. This characteristic is usually called urban canyons.

A possible solution to increase the precision of GPS system is to rely on more than one navigation systems, such as GLONASS, Galileo, BeiDou-2. Other possibility is to use more than one GPS receivers. The joint use of RTK-GPS and DGPS systems can indeed provide centimetre accuracy [161]. However, also in this case, the position accuracy can be significantly affected if the connection with the reference fixed GPS receiver is lost.

A reliable solution to the uncertain quality of the GPS positioning system is to fuse together GPS data with data from other sensors, both vehicle motion sensors, such as wheel odometry and inertial navigation sensors, and other environmental perception sensors, such as RADARs, LiDAR, ultrasonic sensors and vision sensors. The fusion of GPS and of the other sensors, thanks to their complementary characteristics, can let to achieve a robust and accurate positioning system [147], [188].

Several research works focused indeed on possible approaches to increase accuracy, integrity and reliability of GPS system. In [160], an approach for complementing GPS is proposed based on dead reckoning methods and exploiting odometer sensors and other inertial navigation sensors. The localization system presented in [148] relies on two types of GPS systems, a RTK-GPS and a DGPS, and on an IMU. Also in [161], the GPS system was used together with an IMU. Instead in [188], in addition to motion sensors, map matching and perception sensors, such as cameras, RADARs and LiDARs, are also used to enhance the positioning system. In particular lanes and crosswalk information gathered by the visual perception system are used, respectively, to correct the lateral and longitudinal errors. Another approach to improve GPS localization and to obviate to GPS blackout is visual odometry [149], [183].

9.2.2 Map-based localization

Other widely exploited localization methods for self-driving cars is map matching. Indeed, highly accurate maps, containing significantly more information with respect to current commercial digital maps, can be used in autonomous driving for the localization task. For example, information about number of lanes, their width are provided by maps and they can be used together with vision sensors to improve vehicle's position accuracy. Perception sensors are indeed used to create in advance a three-dimensional representation of the environment, i.e. a 3D digital map, and these maps are then exploited during navigation to localize the vehicle comparing particular features of current environment with those that can be identified in the maps [151], [162].

Sensors for mapping and features detection can be stereo cameras [151], [183], LiDAR [162] or other perception sensors, such as RADARs, that can sense and model the environment with high precision and resolution. However, the map-matching presents also some drawbacks. Indeed, the complexity of the urban environment and the presence of several non-static objects, such as cars, bicycles, pedestrians, make the matching process unreliable and possible affected by position uncertainties [183]. The map building is indeed a very critical aspect for map-matching localization approach. A possible alternative is to use SLAM approaches either based on active sensors, such as LiDAR or RADARs, or on vision sensors. The use of the latter seems to be a more viable solutions due to their lower cost and energy consumption [163].

9.2.3 Road and lane detection

The road and the lanes detection assumes a relevant importance in the localization of self-driving road vehicles for two main reasons: on the one hand, both road surface and lane markings can provide useful information for enhancing the vehicle position accuracy; on the other hand, the lane marks constitute strong constraints for the manoeuvres. The lane detection is a challenging problem since several factors affect the lane markings. Markings can be difficult to be identified due to the presence of other vehicles or other objects, such as snow or fallen leaves, and the possible different colours and shapes of lane markings add further complexity.

Moreover, shadows or varying lighting conditions make difficult to easily identify the markings [151], [166]. More in general, the main aim of the road surface detection is the understanding of which part of the image represents a drivable road surface. Shadows on the asphalt or low lighting condition such as during night period can make difficult a correct identification of the surface. Further complexity in the road identification is present if the car is supposed to drive in unstructured environment. The road detection is easier, but still challenging, in structured environment where there are asphalted roads. Vision-based approaches are used to sense the environment and image processing algorithms are used to classify image pixels to be part or not of the road surface [193], [194]. Some proposals also include LiDAR in road detection system [181].

Several methods for lane detection have been introduced so far in the literature. Several of them exploit visual sensors. In [166], the lane detection is performed using visual sensors and a machine learning approach. Instead, LiDAR is the only sensor used in [190] where different reflectiveness of the road surface and of lane markings are exploited for identifying lanes.

Different cameras can be used in road and lane detection. Monocular camera can achieve a rich representation of the field of view, but they experience critical issues with no good lighting condition and they cannot provide three-dimensional representation of the environment. Stereovision cameras can instead provide a three-dimensional representation, but a dense structure requires time and it may be not so precise. To overcome these limitations, LiDARs are typically jointly used with cameras. LiDARs can provide very precise distance information, but they can provide limited information about texture and colours, that instead cameras can provide [181]. For example, in [185] a video and LiDAR based system for lane detection is introduced. A visual camera and a LiDAR are used in [173] to identify both road surface and the lanes.

9.2.4 Cooperative vehicle positioning

The cooperativeness concept introduced by ITS can provide a further approach for cars' localization. Indeed, connected cars, exploiting their communication capabilities, can broadcast messages specifying their position. Each car can use these messages as active beacons and, knowing the distances between itself and the nearby cars, can use trilateration techniques to compute or refine its position.

Time of Flight ranging techniques or the use of ranging sensors such as RADARs or LiDARs can provide the distance information. In [186] and in [187], cooperative positioning is achieved by using RADAR as ranging device. In both cases, it is assumed that cars are equipped with GPS-based system that is used to perform an initial estimate of the position.

9.3 Obstacle detection

The obstacle detection in self-driving cars is a very challenging and fundamental task. Cars are indeed required to navigate in an environment where static and dynamic objects are present. In particular, vulnerable road users, such as pedestrians and bicycles, are sharing the environment and it is essential to ensure to them the highest possible level of safety. The perception system has to correctly detect and classify all objects and other road users to avoid collisions and mitigate situation of risks [150].

Some specific type of objects, such as road traffic signs, traffic lights or markings, are required to be understood. For this reason, cameras are fundamental to be used in the car's perception system since they can mimic the behaviour of human vision and they can differentiate, using image processing algorithms, the different shapes and colours of the road traffic signs [146]. Furthermore, some specificities of road signs must be considered when developing the perception system. For example, the recognition of traffic lights is possible only if there is a camera with a viewing angle of up to 120 degrees that permits to see traffic light in front of the vehicle [151]. The recognition of pedestrian and bicycles as such can also improve the behaviours of autonomous cars allowing them to perform safer and more appropriate manoeuvres [162].

Perception systems typically rely on several different type of sensors that are complementary since they can provide reliable information in different driving situations that can be characterized by particular weather and lighting conditions or by other criticalities. Visual sensors and active sensors, such as LiDARs and RADARs, are usually used together since the first can provide accurate spatial information, but limited functionalities in case of bad weather, while the latter are more robust to critical weather condition and they can provide more precise depth information. In perception systems, the range sensors, that are RADARs and LiDARs, are used to identify and track obstacle, while visual sensors are also employed to recognize and classify the different obstacles [148], [150], [182].

RADARs and ultrasonic sensors are also employed in the vehicles' perception system. The RADARs are mainly categorized according to their perception range. They can be short-range and wide-angle, mid-range and wide-angle, and long-range and narrow-angle. Short-range sensors of about 20–30 m are used for crashing detection and blind spot detection, while long-range sensors of 200 m are employed for cruise control and similar applications. Ultrasonic sensors are instead mainly used for very short-range applications such as parking [146], [151].

The perception system is then conceived to detect all the surrounding of the vehicle employing sensors with different ranges and fields of view. An example is shown in Figure 13 where the coverage of the perception system of the experimental vehicle Bertha Benz is shown. Other example is shown Figure 14 where the perception system of the Tesla car is detailed [152].

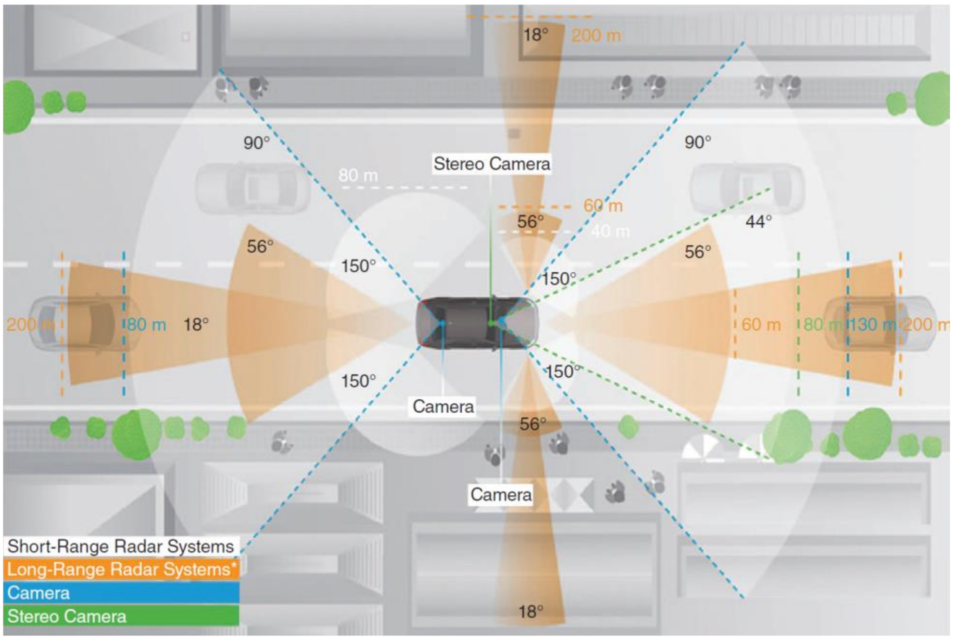


Figure 13 – Bertha Benz experimental vehicle with range and field of view of its perception sensors [151].

Figure 14 – Perception system of Tesla car [152].

Large research has been performed concerning obstacle detection and identification for self-driving cars. Research works are mainly differentiated by the sensors employed. Some examples are introduced in the following.

For example, in [161] several cameras and LiDARs are used for objects detection. In particular, two monochrome cameras have been used to identify the objects exploiting a machine learning approach, while a colour camera identified specific colour features of the objects. LiDARs have been employed to solve the perception limitations of camera. LiDAR, assisted by an integrated IMU and GPS unit, is instead used to detect obstacles in [164]. Detailed analysis of other works concerning three-dimensional perception systems for the automotive use are introduced in [164]. Visual odometry and stereo-vision is employed in [165] for achieving a three-dimensional detection of the obstacles. An obstacle detection based on LiDAR is proposed in [191], while LiDAR and camera information are combined for car detection in [176]. A car detection system that relies only on monocular vision is instead presented in [177]. RADARs are also exploited in perception system. In [178] a car detection system based on stereo camera and RADAR is proposed. An object detection system, based on RADAR and binocular camera, is introduced in [182]. An alternative approach to obstacle detection is instead proposed in [184] where it is proposed to detect, using just a single camera, the obstacle-free space where cars can drive without any risk of collision.

Large attention is also devoted to specific task of pedestrian recognition. In [150], pedestrians in urban scenarios are detected using a system made by a LiDAR and a camera. Several other works concerning pedestrian recognition are introduced in [150]. A stereovision-based system is instead presented in [175]. Neural network approach is presented in [189]. LiDAR and a machine learning approach are instead used in [192]. Pedestrian detection in night time is tackled in [195] where infrared vision sensors are exploited.

Another critical task for autonomous car is managing the approach to intersection. Two main approaches have been proposed to assist the perception system of the vehicle for intersection crossing. One solution is to have fixed sensors, either cameras or LiDARs, which detect all road users in the intersection and determine their motion state, i.e. speed, heading, position, and they distribute this information to ease the trajectory planning of self-driving cars [159]. Other possible solution is instead to rely on vehicle-to-vehicle (V2V) for a cooperative collision avoidance system [180]. In the latter case, the solution can be effective if all road users are able to communicate, while in the first case even if a road user cannot communicate its position it can be identified by the fixed monitoring infrastructure.

A further method that can be exploited by self-driving cars to detect and avoid obstacles is to rely on the cooperativeness of the other road users. As previously introduced at the beginning of this section, road users in an ITS can exchange messages using wireless communications to inform about their presence, to alert about obstacles on the roads and other dangers and to manage efficiently critical situations such as intersection crossing [169]. A cooperative collision avoidance system can thus complement the perception system of autonomous cars.

9.4 Communication

The intra-vehicle communication is typically performed using the CAN bus that is already available on-board of the current vehicles. A new communication architecture FlexRay [168], more performing and more reliable than the CAN bus, is expected to be used in the next future [167].

Inter-vehicle communications constitute themselves a huge research topic. The most consolidated approach is that of vehicular ad hoc networks (VANETs) which relies on the IEEE 802.11p standard which is devoted to dedicated short-range communications in vehicular environments. A very wide literature (dating back to at least 10 years ago) can be found, as well as multiple standardization frameworks can be found on them (IEEE, ETSI, ISO, …).

Since, in this field, things are known, we will highlight only the main aspects which can be relevant to ASTRail future analyses. For the remaining aspects, and further detailed explanations about VANETs and IEEE 802.11p, we suggest [169].

VANETs rely on the following main concepts:

- Unlicensed but reserved bandwidth in the 5.9 GHz range.
- Some differences between the EU and US standards.
- Possibility to communicate without a fixed infrastructure, so to avoid issues on extensive installations and avoid OPEX.
- Continuous periodic transmissions of messages by each vehicle (indicating its position and kinematics data and event-driven transmission of messages, for safety purposes.
- Management of the privacy in the communications.

Other aspects are still being debated, such as:

- If and how messages should be forwarded;
- how to cope with medium congestions;
- the management of the multiple channel reserved in the target bandwidth.

Recently, significant effort has been also devoted to enhance current mobile networks for supporting vehicular communications. The 3GPP standardization body has indeed tackled to extend the support of LTE to vehicular communications [170], while development of practical implementations of LTE for vehicular communications are currently undergoing (they are talking about LTEv) [171], [172].

At the current stage, it is not clear if, in the end, VANETs and LTE will coexist or if just one is likely to survive. Apparently, the most critical issue to be solved is that no direct communication between two LTE users is currently possible. The dynamic road environment requires to have very low latency times that can be achieved only with direct communication between end-users and, also, direct communications would solve the issue of requiring a complete coverage of the wireless coverage all over the world.
However, the direct link is something which is currently in the roadmap of LTEv, also in the case of complete absence of infrastructure. If this could be achieved, one would have the chance of putting together the benefits of ad-hoc communications and of a straightforward connection to the Internet backbone and services.

9.5 Standard

The standardization of the technologies and of solutions of autonomous driving are essential for the use of self-driving cars in the real world. Some standards have been already published by SAE (Society of Automotive Engineers) and ISO. These standards are mainly related to the specifications of operating conditions, performance requirements and test procedures of some specific autonomous driving aspects, such as adaptive cruise control, forward vehicle collision warning systems, lane departure and lane change warning systems. However, these standard provide basic definitions without entering into the details of the technological requirements or clarifying some specific aspects of these solutions, due also to the initial developing stage at which these technologies are [154].

SAE has however issued in January 2014 a standard that provides a common taxonomy and definitions for automated driving. The SAE International Standard J3016 “Taxonomy and Definitions for Terms Related to On-Road Motor Vehicle Automated Driving Systems” aims to ease the communication and the collaboration on autonomous driving aspects in both technical and policy domains [145].

Six levels of driving automation have been defined in the J3016. Level 0 corresponds to no automation and level 5 to full autonomous systems. Intermediate levels correspond to partial automation where human driver is still required to perform some actions or to intervene at request of the automation system. The description of each level indicates the minimum capabilities that the automatic driving system should have in that level. In Figure 15, a detailed description of each level of automation is shown [145].

SAE level	Name	Narrative Definition	Execution of Steering and Acceleration/ Deceleration	*Monitoring* of Driving Environment	Fallback Performance of *Dynamic Driving Task*	System Capability *(Driving Modes)*
***Human driver* monitors the driving environment**						
0	**No Automation**	the full-time performance by the *human driver* of all aspects of the *dynamic driving task*, even when enhanced by warning or intervention systems	Human driver	Human driver	Human driver	n/a
1	**Driver Assistance**	the *driving mode*-specific execution by a driver assistance system of either steering or acceleration/deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	Human driver and system	Human driver	Human driver	Some driving modes
2	**Partial Automation**	the *driving mode*-specific execution by one or more driver assistance systems of both steering and acceleration/ deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	**System**	Human driver	Human driver	Some driving modes
***Automated driving system* ("system") monitors the driving environment**						
3	**Conditional Automation**	the *driving mode*-specific performance by an *automated driving system* of all aspects of the dynamic driving task with the expectation that the *human driver* will respond appropriately to a *request to intervene*	System	**System**	Human driver	Some driving modes
4	**High Automation**	the *driving mode*-specific performance by an automated driving system of all aspects of the *dynamic driving task*, even if a *human driver* does not respond appropriately to a *request to intervene*	System	System	**System**	Some driving modes
5	**Full Automation**	the full-time performance by an *automated driving system* of all aspects of the *dynamic driving task* under all roadway and environmental conditions that can be managed by a *human driver*	System	System	System	**All driving modes**

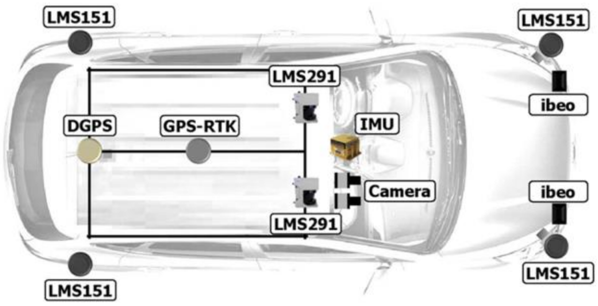
Figure 15 – SAE International standard J3016, Taxonomy and Definitions for Terms Related to On-Road Motor Vehicle Automated Driving Systems [145].

9.6 Prototypes and concepts

Many prototypes of self-driving cars have been found during the literature review. Moreover, several concepts are being also developed by different enterprise, as already mentioned. Few details about enterprise projects are however available. In the following, we report few examples of car prototypes not aiming at providing an exhaustive and complete list of all autonomous cars prototypes that are being developed.

In [148], autonomous car A1 is used for self-driving experimentation. The A1 car is shown in Figure 16. Odometry sensors, such as including wheel-speed sensors, a steering-wheel-angle sensor, and a yaw-rate sensor, were already on-board the vehicle since used by the electronics stability control system and they were accessible through the CAN. An IMU has been installed to increase the motion state measurements availability. A RTK-GPS and a DGPS receivers have been used for retrieving absolute positioning. One colour camera and three monocameras are installed to identify objects in the environment.

Eight LiDARs are installed on A1: two of them (Ibeo LUX) are installed in front of the car and they are used to detect objects up to 200 m away in optimal conditions, four LiDARs (LMS151) are installed for each corner of the vehicle and two LiDARs are installed on the roof of the vehicle to scan vertically to the ground.



(a) **(b)**

Figure 16 – (a) A1 autonomous car prototype, (b) map of sensors installed on-board of the A1 car [148].

Advanced self-driving cars are those developed by Tesla [152]. Due to regulations restrictions Tesla cars cannot be commercialized as fully autonomous cars, i.e. the fifth level SAE. A human driver must always be ready to take the control of the car. However, all Tesla models are provided with sensors and equipment that can implement autonomous driving. Advantage of this approach is the possibility to collect data about autonomous driving feature without the need of testing.

Detailed description of all sensors employed for the perception system is available. Instead, no significant information can be found about the localization system of Tesla cars. In Figure 14, the perception system of Tesla cars is shown. Eight cameras are used to provide field of view of 360 degrees. In particular, a narrow forward camera is installed to provide up to 250 m range for focused, long-range applications, while a wide camera with 120 degrees fisheye lens is used to detect traffic lights and obstacles close to the car., obstacles cutting into the path of travel and objects at close range. Other cameras are devoted to 90 degrees forward looking application, rearward looking side to monitor blind spots on the sides of the car and rear view mostly for parking applications.

Perception systems is completed with eight ultrasonic sensors for close-range objects detection and with a RADAR for effective forward detection in case of degraded environmental and weather conditions, such as dust, rain, snow, and under cars.

Other autonomous driving car development project to mention is the one carried on by Google-Waymo [157] . Not detailed information is publicly available about the localization and the perception systems employed by the Waymo car. Most evident characteristic is the use of LiDAR. It seems indeed that Waymo cars mainly rely for the navigation on detailed maps of the driving environment, previously recorded, using LiDAR [151], [158].

10 Autonomous driving trains

There are various degrees of automation for autonomous driving trains and each author, supplier, Train Operating Company, Infrastructure Manager, uses their own language and abbreviations. The Operation Concepts formally defined by European Railway Operators (EEIG) cover all Grades of Automation (GoA):

Grade of Automation	Door closure	Setting train in motion	Stopping train	Degraded operation in case of disruption
GoA1: Non- automated train operation	Driver	Driver	Driver	Driver
GoA2: Semi-automated train operation	Driver	Automatic	Automatic	Driver
GoA3: Driverless train operation	Attendant	Automatic	Automatic	Attendant
GoA4: Unattended train operation	Automatic	Automatic	Automatic	Automatic

Table 1 - Grades of Automation on Railways.

The current state of the autonomous driving on Railways is that, despite existing of CBTC based proprietary solution on metro lines which achieve the highest level of the Automatic Driving (GoA 4 or unattended driving), GoA4, 3 and even 2 does not exist on main lines.
GoA1 (Automatic Train Protection) is archived in ERTMS applications.

10.1 Technologies and enabling sensors

10.1.1 Automatic train operation system

This kind of system consists on an on board controller which performs the actions usually performed by a driver in conventional train operation. An Automatic Train Control system provides a high level of train safety, allowing one to increase the running speed and the line capacity. These systems automatically perform their monitoring and control action in order to prevent against the consequences of driver errors.

Automatic Train Operation systems collaborate with ATP (Automatic Train Protection) and ATS (Automatic Train Supervision). ATP is the safety system which ensures that trains remain at a safe distance and have sufficient warning to allow them to stop without colliding with another train. The ATS can help dispatcher supervise and manage train operation. ATO is concerned on the parts of train operation related to station stops and starts, punctuality, comfort and energy saving. ATO will receive commands from ATS to adjust train speed and will work under the limitation of ATP.
A basic diagram of the architecture of ATO systems is represented in Figure 17.

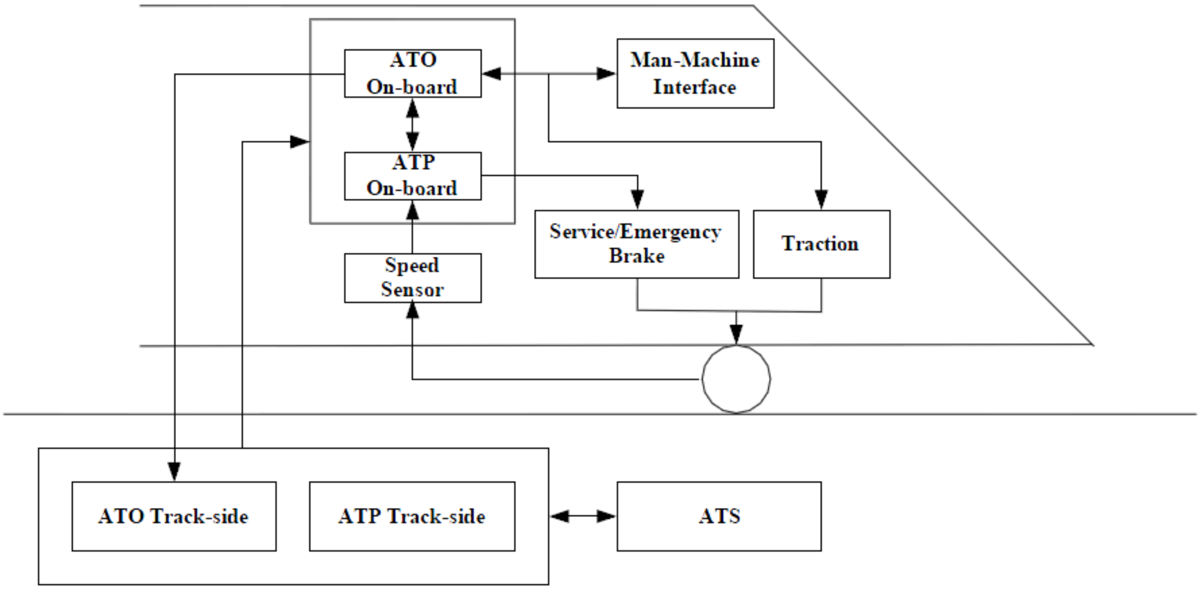


Figure 17 – Basic architecture of ATO system [196].

The basic requirement of ATO is to adjust train speed in operation and make train stop accurately at a station when the train approaches it. ATO should not only adjust train speed to reach the requirement of schedule, but also achieve excellent performance in punctuality, comfort and energy saving so far. The following points in Table 2 are the main requirements for the ATO performance.

ATO Requirements	Description
High-Efficiency	This is the original purpose for using ATO system. ATO can improve the efficiency of the whole system and increase the capacity of line.
Punctuality	This point is an important character for railway traffic, especially for urban mass transport. Trains run under the schedule. When a train is delayed, it needs ATO to adjust train's speed and prevent train from disordered operation.
Energy-Saving	The energy cost of the manual operation is usually more than automatic operation. Therefore, energy-efficient train control for ATO is an important approach to saving energy
Comfort	In order to improve comfort, the change of acceleration and deceleration should be infrequent and the value should be small. The total number and the maximum of acceleration and deceleration during a trip
Stop-Accuracy	For urban mass transport, stop-accuracy is also an important character, especially for stations with PSD (Platform Screen Door). Inaccurate stop will obstruct passengers taking on and off.

Table 2 - ATO requirements [196].

In order to provide a correct performance ATO systems require information about:

- The current position and the line gradient;
- The distance to targets (point in correspondence of which speed restrictions have to be achieved)
- The target speed (i.e. the speed that has not to be exceeded when the train passes through a target point).

This information is communicated to the train with the aid of fixed balises, virtual balises or another kind of absolute information. Between two consecutive information points on the line, the on-board subsystem performs a dead reckoning of the speed and the travelled distance and calculates:

- The minimum distance that allows to respect the speed restrictions at the next objective points: this value depends on the actual train speed, on the braking parameters and on the objective speed;
- The distance to the next information points.

If the difference between the distance to one or more of the next objective points and the distance that allows to respect the speed restriction is smaller than a fixed value, the on-board subsystem intervenes, for instance by activating the emergency braking. Figure 18 represents the information flow of an ATO system.

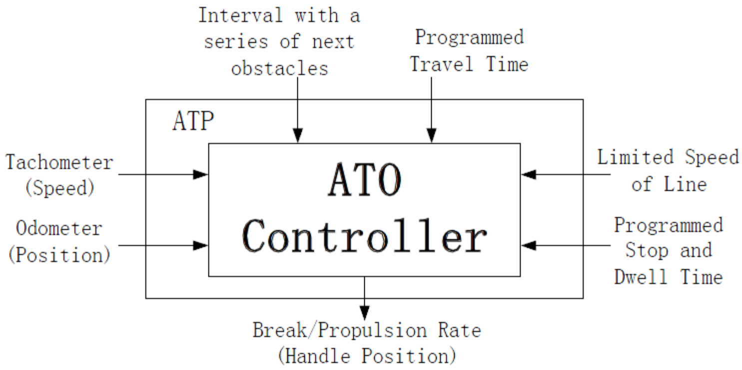


Figure 18 – ATO Controller model [196].

10.1.2 Odometry system for ATO

The main information required by ATO controller is provided by the odometry system. For this reason, the odometry system has a very important function in ATO systems.

The odometry system evaluates the speed and train position during its run. It includes a series of sensors (for example wheel angular speed sensors, Doppler RADAR, longitudinal accelerometer) and a procedure (named “Odometry Algorithm”), that fuses data from the track and from the sensors mounted on the train in order to perform the odometrical estimation. The values calculated by the odometrical system are communicated to the ATP on board module, that compares them with the braking curves and decides an eventual intervention. The odometry system performance, in terms of accuracy of speed and distance estimation, may affect the whole ATP system performance.

If the odometry system tends to under-estimate the speed and the current position, the safety of the ATP system may be affected, since the train “thinks” to have a speed lower than the real one and/or to be at a distance from the objective greater than the real one, then a possible intervention of the control system could be delayed and the objective (for example stopping at a red signal) could be not respected.
On the other hand, if the odometry system tends to over-estimate the speed and the current position, the efficiency of the ATP system may be affected, in this case the train “thinks” to have a speed greater than the real one and/or to be at a distance from the objective shorter than the real one, then a possible intervention of the control system or could be not necessary or anticipated. For these reasons a particular care has to be put in the design and testing of such devices.

The performance of dead reckoning by means of odometry (in terms of precision in the estimation of speed and travelled distance) depends on how the information from different types of sensors is fused. For example, the estimation obtained with the measure of one or more wheel speeds may fail if degraded adhesion in the wheel-rail interaction occurs, due to rain, fog, ice, leaves, and so on, and the train is accelerating or braking, i.e. when pure rolling conditions between the wheel and the rail do not hold anymore, and macroscopic sliding occurs on one or more of the axles equipped with odometry sensors. The accelerometer sensor is sensitive to the inclination with respect to the horizontal direction, so it can give erroneous information in presence of a line gradient or pitch motion of the vehicle where it is mounted.

Sensors	Description	Limitations
Wheel speed sensor	Measures the wheel angular speed, widely used in the on-board subsystems.	Parameters limiting the accuracy of this kind of measure are: -the resolution of the sensor, -the sampling time, -electrical noise, -mechanical imperfections such as backlash -slip and slide between the wheel and track
Doppler Radar	Measures the relative speed between itself and a surface by detecting the frequency shift of a signal.	The measure may be affected by some possible sources of error: -very smooth surfaces may cause loss of discrimination in the reflected signal, -change in the radiation angle caused by the pitch and tilting motion of the body on which the sensor is mounted, -existence of vibration can create noise in the data, -existence of radar noise and bias errors.
Accelerometer	Measures the linear acceleration of the vehicle, by integrating the acceleration signals both speed and position data can be derived. For this measurement method the exact initial values of speed and position are required.	The measure is sensitive to the angular position of the sensor and then to the motion of the body on which it is mounted. For example, if a mono-axial accelerometer is used to measure the longitudinal acceleration of the train, the measure will be affected by the pitch motion of the vehicle and by the line gradient.

Table 3 - Sensors frequently used in railway system.

In order to obtain a reliable odometrical estimation and to prevent system failure the use of different types of sensors is necessary. The different measures have to be combined, the system has to identify the conditions in which the sensors are operating and to choose the measure that, in every situation, has the maximum reliability.

The odometry algorithm is then designed to perform an estimation of the state of the system (it has to be able to recognize the situations in which one or more of the sensor measures are affected by an error due to the operational conditions) and to choose for every condition, the estimation procedure that with the greater probability is the more corrected.

The Table 4 summarizes the sensitivity of each sensor with respect to particular operational conditions.

	Accelerometer	Angular speed sensor	Doppler Radar
Adhesion between the wheels and the rail	NO	YES	It is not possible to find a relation between the Doppler radar sensor performance and these conditions
WSP and pneumatic brake dynamics	NO	YES	
WSP and electric brake	NO	YES	
Traction system, traction control (anti slip device)	NO	YES	
Mechanical properties of the vehicle and of the traction system	NO	YES	
Information on line gradient	YES	NO	

	Accelerometer	Angular speed sensor	Doppler Radar
Vehicle pitch motion	YES	NO	YES
Vehicle roll-tiling	NO	NO	YES
Reflecting properties of the line	NO	NO	YES
Presence of contaminants (snow, water, dead leaves etc.)	NO	NO	YES

Table 4 - Sensor measure sensitivities [197].

10.1.3 Automatic Train Protection system

The meaning of a train protection system is to reduce the risks connected to driver failure to comply with railway signals. An automatic train protection system continually checks that the actual speed of a train is compatible with the permitted speed, as allowed by signalling [198].
The speed may be limited by line profile or signals indication, that is, the need to protect routes of other trains and track related constraints. If the allowable speed is exceeded, a brake application is invoked until the speed is brought within the required limit or the train is stopped.

The maximum allowable speed (MAS) can vary from 0 Km/h to the track's MAS, and is determined by variable factors such as presence of maintenance crews on Right Of Way (ROW), train headways and the relative distance between the train and home signals. Constant communications between train on-board computer, wayside instrumentation and the control centre help determine MAS.
ATP is basically composed by two modules: train detection (localization of the train) and movement authority (proceeding authorization to the next check point).

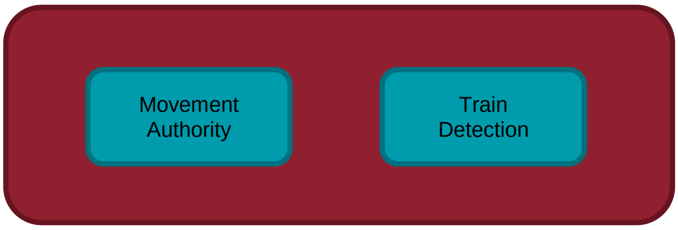


Figure 19 – Basic ATP modules.

Technologies adopted for warning and train stop systems include combinations of permanent magnets and electromagnets, inductive polarity-changing responders, coded beacons and simply coded track circuits.
More recently, ATP systems have been developed to enforce speed limits and movement authorities at the full range of restrictive signals, with and without line-side signals and including permanent and temporary line speed limits. Driving is still manual, but speed limits are always enforced. Degraded modes though invariably include low speed driving on sight.

Two types of ATP can be identified: intermittent (using balises) and continuous (using electrical inductive coupling). Most metro applications use continuous systems in conjunction with ATO. Intermittent ATPs are typically less expensive, but information can only be updated at discrete points: this could affect optimum speed performances.

10.1.3.1 European Train Control System (ETCS)

European Train Control and Command System (ETCS) is an automatic train protection system, based on cab signalling and spot and/or continuous track to train data transmission, promoted by the European Commission for use throughout Europe. It ensures trains operate safely at all times in providing safe movement authority directly to the driver through the cab display and in continuously monitoring the driver's actions.

ETCS is the signalling component of the European Rail Traffic Management System (ERTMS), a European standard that aims to replace legacy national ATPs and guarantees interoperability across Europe [199].
The ETCS specification has three substantially different ATP operating levels allowing a stepped transition from conventional line-side signalling to a full moving block concept, with some incremental additions. The levels provide full speed supervision and varying amounts of in-cab information, throughout a train's journey.

10.1.1 ATO implementation in CBTC system

According to standard IEEE 1474.1-2004, a CBTC system shall, as a minimum, be capable of providing all of the ATO functions as defined below, to automatically operate trains in accordance with prescribed operating criteria within the safety constraints imposed by ATP.
The CBTC wayside-to-train and train-to-wayside data communications interface shall be sufficient to support all required ATO functions:

- *Automatic speed regulation*

  The starting, stopping, and speed regulation of the train as it travels along the track shall be automatically controlled by a CBTC system so that the speed, acceleration, deceleration, and jerk rates are within specified passenger comfort limits (as defined by the authority having jurisdiction) and the train speed is below the overspeed limits imposed by ATP.
  Station stopping accuracy shall be as specified by the authority having jurisdiction.
  A CBTC system shall support multiple ATO speeds, acceleration, and service brake rates in accordance with the train operator (if present) or ATS inputs.
- *Platform berthing control*

  A CBTC system shall be capable of implementing platform berthing control modes, whatever is the platform length with respect to train length.
- *Door control*

  A CBTC system shall be capable of automatically controlling train doors (and platform edge doors, where fitted) during passenger boarding and discharging.

In the following table typical ranges for certain CBTC parameters for general guidance are shown, according to standard IEEE 1474.1-2004:

Parameter	Typical range
Maximum number of trains that can be processed by a single wayside controller	10 to 40 trains
Resolution of measured train location (i.e., as reported to establish movement authority limits for a following train for ATP purposes)	± 0.25 m to ± 6.25 m (± 10 in to ± 20 ft)
Accuracy of measured train location during normal (non-degraded) operations (i.e., maximum error in reported train location for ATP purposes)	± 5 m to ± 10 m (± 16 ft to ± 33 ft)
Accuracy of measured train location for programmed station stop (ATO) purposes—without platform edge doors	± 0.25 m (± 10 in)
Accuracy of measured train location for programmed station stop (ATO) purposes—with platform edge doors	± 0.05 m (± 2 in)
Resolution of train movement authority limits	± 0.25 m to ± 6.25 m (± 10 in to ± 20 ft)

Parameter	Typical range
Resolution of train speed measurement for ATP purposes	± 0.5 km/h to ± 2 km/h (± 0.3 mi/h to ± 1.25 mi/h)
Accuracy of train speed measurement for ATP purposes	± 3 km/h (± 2 mi/h)
Resolution of train speed commands (e.g., civil speed limits)	±0.5 km/h to ± 5 km/h
Resolution of train speed commands (e.g., civil speed limits)	±0.5 km/h to ± 5 km/h (± 0.3 mi/h to ± 3 mi/h)
Train-to-wayside message communication delays	0.5 s to 2 s (nominal)
Wayside-to-train message communication delays	0.5 s to 2 s (nominal)
Wayside CBTC equipment reaction times	0.07 s to 1 s (nominal)
Train-borne CBTC equipment reaction times	0.07 s to 0.75 s (nominal)
Rollback detection criteria	0.5 m to 2 m (± 20 in to ± 6.5 ft)
Zero speed detection criteria	< 1 km/h to <3 km/h for 2 s (< 0.6 mi/h to < 2 mi/h for 2 s)

Table 5 - typical ranges for CBTC parameters [200].

11 Conclusions

The survey on state-of-the-art autonomous driving technologies has been conducted in task T3.1 of ASTRail WP3. This task has the objective to provide an overview of mature and cutting-edge technological solutions that are introduced for vehicle autonomous driving.

The survey covered several different application fields where autonomous driving vehicles have been introduced. These application fields are the agriculture, the industrial environment, the maritime, the avionic, the automotive and the railway sectors. Scientific research, industrial research and commercial deployment have been considered during the survey.

Main functionalities, which are implemented by each autonomous driving system, have been identified and analysed. An autonomous driving system is based on trajectory planning, navigation, guidance and control functionalities. Trajectory planning has not been considered in the survey since of partial interest in the railway field, being trains constrained by tracks and timings already defined by a centralized control system. Navigation is a challenging task in which the vehicle localization and the perception of the surrounding environment are executed. The survey focused on navigation-related technological solutions.
Guidance and control mainly involve the definition of mathematical models of the vehicle system. Both of them are strictly related to vehicles' characteristics, i.e. physical actuators and motion characteristics, and to the information received by the navigation system. This information is not yet fixed, since navigation sensors are not currently defined, being also object of the survey. For these reasons, the survey did not focus on the control and guidance aspects of the autonomous driving system which are left for future studies.

A first outcome of the survey is that several of the identified technological solutions for the navigation task are equally adopted in most of the different application fields. This aspect foresees a good possibility to have some technologies that can be reused also in the railway sector. Hereafter, a brief summary about the technologies employed for the localization and the environment perception systems is introduced.

Satellite positioning and dead reckoning methods are the most widely adopted localization techniques. GPS, or enhanced versions of GPS such as Real-Time Kinematic GPS and Differential GPS, provides absolution positioning of the vehicle. Odometry and inertial navigation are the mostly used methods for dead reckoning that provides relative vehicle positioning. Dead reckoning is used to increase the accuracy and the reliability of GPS system.

Another approach adopted to increase the accuracy of the localization is the employment of visual cameras and of active perception sensors, such as RADAR or LiDAR. These sensors can be used to identify particular features in the environment and to estimate the relative motion of the vehicle with respect to these features. More complex approach is to construct a representation of the environment that can be exploited in map-based navigation approaches.

The perception system, that is used to detect potential obstacles, typically relies on several types of sensors. Cameras, RADARs, LiDARs are the most common sensors used. These sensors are usually jointly used since each of them presents different operating advantages or drawbacks. Visual sensors can provide a very detailed spatial resolution, but their performance is strongly affected by bad weather conditions and by low lighting conditions. Furthermore, depth information can be difficulty provided. Only stereovision cameras are able to provide three-dimensional information, but at high computational cost. RADARs and LiDARs can instead provide well detailed depth information, but they cannot recognize objects. Furthermore, since they are active sensors, they are typically more expensive and more power consuming than visual cameras. Due to these complementarity characteristic, several types of sensors are typically used in the perception system.

Considering the last remark, it is possible to confirm that the survey has identified the widespread use of several different types of sensors for the same task. This holds for both localization and perception tasks. Also, considering the plethora of sensors met in each solution, multi-sensor data fusion approach is also commonly adopted to improve reliability, robustness and accuracy.

An additional possible approach for localization and obstacle detection tasks consists in the cooperativeness among vehicles. Wireless-connected vehicles can broadcast messages to inform about their status, such as position, speed, direction, and to provide information about obstacles and other possible risks. This approach is mostly expected to be used in the automotive sector. This additional source of information can complement the other sensors enhancing the performance of the overall autonomous driving system.

All in all, the survey collected detailed information about several technological solutions for autonomous driving and their enabling sensors. Main advantages and drawbacks impacting on the performance of these solutions have been identified. The next step is to identify which main implementation characteristics of the technologies are valid for the railway field. Following, the feasible autonomous driving technologies for the railways will then be evaluated and the most suited ones will be assessed.

Acronyms

Acronym	Explanation
3GPP	3rd Generation Partnership Project
ADS-B	Automatic Dependent Surveillance – Broadcast
AGV	Automatic Guided Vehicles
AIS	Automatic Identification System
AR-code	Augmented Reality-code
ASTM	American Society for Testing and Materials
ASV	Autonomous Surface Vehicle
ATO	Automatic Train Operation
ATP	Automatic Train Protection
ATS	Automatic Train Supervision
AUV	Autonomous Underwater Vehicle
CAN	Controller Area Network
CBTC	Communication Based Train Control
COLREGs	International Regulations for Preventing Collisions at Sea
COSPAS	COsmicheskaya Sisteyama Poiska Avariynich Sudov
CPU	Central Processing Unit
DGPS	Differential GPS
DSC	Digital Selective Call
DVL	Doppler Velocity Logger
EEIG	European Economic Interest Group(ing)
EPIRB	Emergency Position Indication Radio Beacon
ERTMS	European Rail Traffic Management System
ETCS	European Train Control and Command System
ETSI	European Telecommunications Standards Institute
FP7	Seventh Framework Programme
GLONASS	GLObal NAvigation Satellite System
GMDSS	Global Maritime Distress and Safety System
GNSS	Global Navigation Satellite System
GPS	Global Positioning System

Acronym	Explanation
GoA	Grade of Automation
ICT	Information and Communication Technology
IEEE	Institute of Electrical and Electronics Engineers
IMO	International Maritime Organisation
IMU	Inertial Measurement Unit
INS	Inertial Navigation System
ISO	International Organization for Standardization
ITS	Intelligent Transport System
LiDAR	Light Detection And Ranging
LTE	Long Term Evolution
MAS	Maximum Allowable Speed
MHS	Material Handling Systems
MiR	Mobile Industrial Robots
MUNIN	Maritime Unmanned Navigation through Intelligence in Networks
OPEX	OPerating EXpenditure
QR-code	Quick Response-code
RADAR	RAdio Detection And Ranging
RFID	Radio Frequency Identification
ROW	Right Of Way
RSSI	Received Signal Strength Indication
RTK-GPS	Real-Time Kinematic GPS
SAA	Sense And Avoid
SAE	Society of Automotive Engineers
SARSAT	Search and Rescue Satellite-Aided Tracking
SLAM	Simultaneous Localization And Mapping
SOLAS	International Convention for the Safety of Life At Sea
SONAR	SOund NAvigation and Ranging
TCAS	Traffic Collision Avoidance System
UAV	Unmanned Aerial Vehicle
UHF	Ultra High Frequency

Acronym	Explanation
VANET	Vehicular Ad hoc NETwork
VSAT	Very Small Aperture Terminal
WP	Work Package

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