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Mobile Robots and Autonomous Vehicle Control: A Comprehensive Review of the Advancements and Challenges

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Abstract

Since their inception, mobile robots have enormously changed the landscape of robotics engineering in recent years. Imperatively, the impact of mobile robots has positively transformed many sectors of human endeavors, i.e., complemented and substituted humans in areas where human interactions were difficult, hazardous, and impossible to thrive and operate. In this regard, the contributions of mobile robots to scientific, social, and economic growth, development, and advancement cannot be overlooked, especially through its decades of transition from Industry 3.0 to 4.0 over the years. To achieve maximum benefits from the use of mobile robots across all important facets, their advancements and technologies need to be continuously improved to address all relevant issues with regard to associated challenges in navigation, control, remote sensing, and tele-operability. This paper presents a comprehensive review of selected key areas of mobile robot technology where major advancements have been made and are currently ongoing to solve numerous problems effectively with less human effort. In addition, highlights of the challenges faced by mobile robots and autonomous vehicle control have been extensively discussed and recommendations have been given to enhance the efficient and safe use of mobile robots in the event of a change in task complexity in all essentials of human life.

Keywords: automatic parking, mobile robot technology, multibody vehicle control, navigation and path following, visual-based control systems

1. Introduction

Technological advancements in the field of robotics engineering have experienced considerable growth in recent years. This progressive rate is attributed to the improvements in sensor-based technologies and communication systems, computer vision, and advancements in machine learning and artificial intelligence (AI). Because of this, the narrative of mobile robots since their introduction in the early 1950s has been considered a constant boon to modernity [1]. As the name suggests, mobile robots are a special type of robot that is engineered to have mobility by interacting with the external environment when performing predefined tasks, indicating that these robots are not permanently stationed at a fixed location. Hence, these robots can move around in their immediate surroundings based on their designed locomotive structure or architecture. Based on this premise, mobile robots have been classified into several unique groups because they exhibit biomimetic characteristics. As shown in Figure 1, a general classification of mobile robots based on mobility comprises legged [2], wheeled [3], aerial [4], and underwater [5] mobile robots.

Legged mobile robots are further categorized into bipeds (typically humanoids) and multi-legged (quadrupeds and hexapods) robots [6–8]. Dynamic or hybrid models have been applied to legged robots to enhance their mobility, which involves the attachment of wheels that influences the freedom or degree of motion [9]. Thus, the motion exhibited by wheeled mobile robots (WMRs) is either holonomic [10] or nonholonomic [11]. WMRs are further categorized based on the number of wheels and the wheel design (e.g., caster, Swedish, spherical, and mecanum) employed [12]. These parameters define the type and degree of motion(s) described by the WMRs. In this regard, WMRs include all unmanned ground vehicles (UGVs) [13]. In contrast to the aforementioned types of mobile robots, autonomous underwater vehicles (AUVs) [14] and unmanned aerial vehicles (UAVs) [15] both have different architectures but similar device components (propellers) purposely suited for their operational environment. Characteristically, all of these mobile robots come in various shapes and sizes with miniaturization achieved even at the microscale or nanoscale [16]. The various architectures of mobile robots enable their use in several aspects of human endeavors, mainly in healthcare [17–

19], transportation [20], search and rescue operations [21–23], mineral mining and space explorations [24–26], media communication [27], security and warfare [28–30], domestic and cleaning applications [31–33], agriculture-related and energy-related fields [34–36]. These undisputable benefits reaffirm the projected increase in the use of mobile robots over the years. As a result of this projection, many dynamic improvements have been made in terms of their development encapsulating specifications, required capabilities, and applications. That is, current developments aim to achieve full autonomy, multitasking, remote control, and tele-operability under varying external conditions among other key objectives [37]. Despite the evolving design complexities, recent technologies have focused on providing solutions to enhance the performance and address the safety issues of mobile robots. That is, in terms of localization, detection, communication, collaboration, computation, navigation, mapping, and autonomous control, the advancements in sensor technologies, networks, operating systems (OSs), machine learning, cognitive science, and deep learning algorithms or frameworks have revolutionized the landscape of mobile robot development and operation. Several studies have been conducted across the continents of America, Europe, and Asia to develop new and innovative technologies for mobile robots [38]. Imperatively, the incorporation of technology into mobile robots varies from one class of mobile robots to another based on the purpose, role, or function it was designed for, indicating that the level of sophistication in the design architecture of a particular mobile robot may differ with respect to another. Although this translates directly in terms of the economic value of the mobile robot, there are fundamentally certain key reference areas of mobile robot development that traverse all classes. A typical case is the recognition of their operating environment when performing a predefined task. Moreover, the development of mobile robot architecture would require a processing unit and an OS that oversees the operation of all set tasks [39, 40]. Popular humanoid robots or bipeds, such as Ameca, Sophia, Nadine, Intro, Artemis, Atlas, Jia Jia, Geminoid DK, Pepper, Robonauts, Junco Chihira, and Beomni have embedded central processing units (CPUs) that run a robot operating system (ROS) to achieve its human-like functionalities, especially with regard to movement. Similarly, other types of legged mobile robots (quadrupeds and hexapods) have this or further include graphics processing units (GPUs) or field-programmable gate arrays (FPGAs) in their architecture. Advanced UAVs, such as MQ-9 Reaper, TAI Aksungur, GJ-11 Sharp Sword, and Uvify drones, are no exception. Thus, these UAVs are employed in reconnaissance, delivery services, surveying, and entertainment. Most of the current advanced UAVs are found in the military and the field of astronomy. WMRs, which encapsulate all UGVs, have undergone a series of transformations with regard to their use in everyday life. These types of robots consist of self-driving cars and trucks, exploration rover robots, military robots, and some personal assistance robots. Unmanned underwater vehicles (UUVs), also known as AUVs, have significantly contributed to unearthing the nature of the marine world.

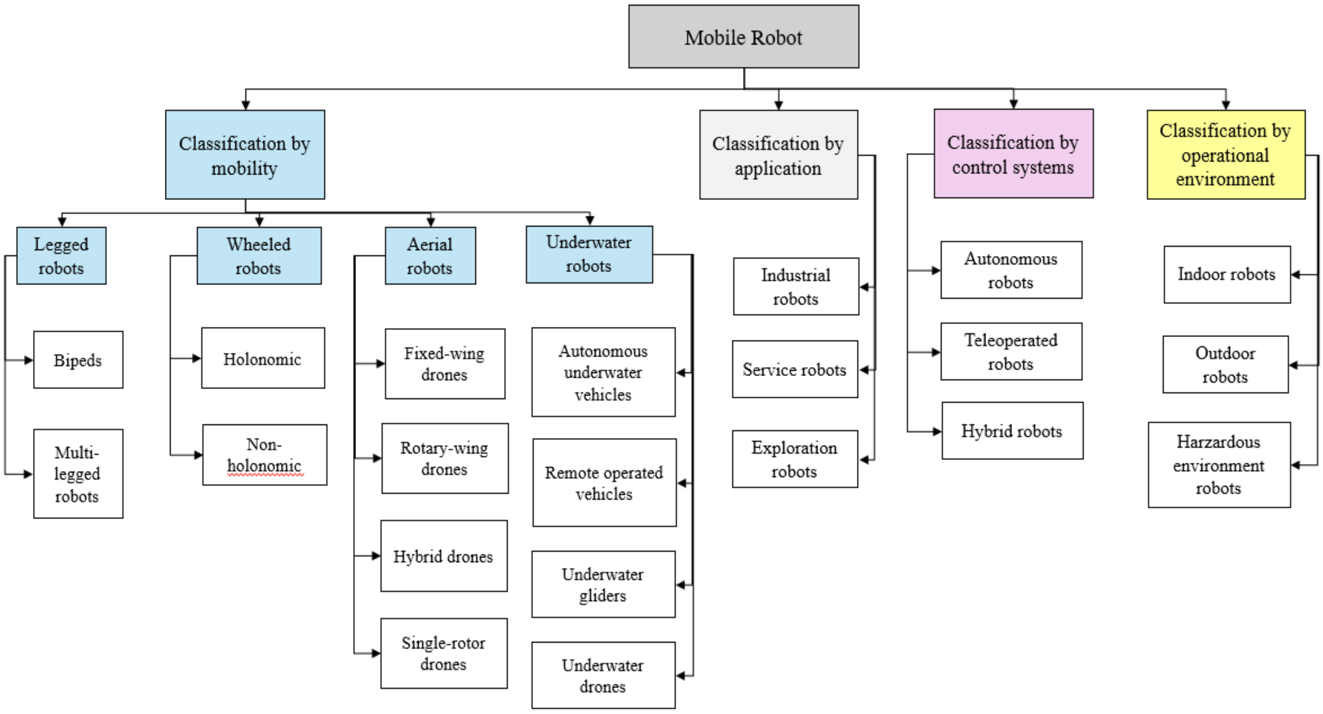

Figure 1. Classification of Mobile Robots

Most of these types of robots are often employed in exploration [41, 42], search and rescue operations [43–45], and warfare [46, 47]. Typical examples of such robots include manned and unmanned submarines, submersibles, autonomous sea drones, and remotely operated vehicles (ROVs) that can operate on the surface and at depths beyond 4.5 km. The unfortunate tragedy of the OceanGate submersible has indicated that exploration by manned underwater vehicles requires strict adherence to safety standards [48]. Considering this circumstance, the imploded parts were recovered using unmanned ROVs, which shows how operable and risk-free mobile robots can be under such depth. Currently, multipurpose mobile robots with several actuators have diverse motion capabilities, such as walking, rolling, and flying. Caltech's M4 robot or multimodal mobility morphobot is a typical example [49]. Therefore, versatility is the trending innovation that seeks to complement the intelligence and maneuverability of upcoming mobile robots because they can act as UGVs at one point, UAVs at another point, and possibly UUVs dependent on the task or challenge confronted with. Fundamentally, the improvements in the hardware and imbibition of the software have positively enhanced and influenced the intelligence of these robots [50]. In dealing with more complex tasks and operating conditions, the hardware components in mobile robots are important for the acquisition of data. The data collected are either internal, external, or both, depending on the predefined task. Software algorithms process these sampled data to produce results that are used to make informed decisions to accomplish the assigned task given to the mobile robot. Hence, algorithms that run in mobile robots must leverage the resources available on the hardware. Thus, the level of intelligence possessed by mobile robots determines their level of autonomy. A general classification is presented in Table 1, referring to the intelligence level of autonomous automobiles [51].

Although advancements continue in this domain of robotics engineering, ethical principles that govern the operation of mobile robots as established by Asimov in 1942 based on three fundamental laws remain relevant [52]. The first, second, and third laws are stated as follows:

- A robot should not injure a human being or, through inaction, allow a human being to come to harm.
- A robot must obey any orders given to it by human beings, except where those orders conflict with the first law.
- A robot must protect its existence untill protection does not conflict with the first and second laws.

Driven by the rapid advancements in machine learning technologies aimed at enhancing the capabilities of mobile robots and vehicle control systems, this paper provides a comprehensive review of the key areas of technological progress in these domains.

Table 1. Intelligence Level of Autonomous Automobiles

Level of Autonomy	Description
Level 0	This level indicates the absence of automated driving. Thus, complete manual control of the mobile robot (vehicle) is assumed, although prewarning systems can still be functional.
Level 1	This level represents driver assistance. This level implies that the operator must still maintain control position and awareness at the operated duration.
Level 2	This level depicts partially automated driving whereby cooperative control is needed. In this case, it requires that the operator take control at a point in time.
Level 3	Conditional automated driving is experienced at this level. Here, the vehicle can control itself only under certain conditions.
Level 4	High automated driving is assumed at this level whereby driving is undertaken with fewer restrictions. Thus, operators only act based on occasional hints.
Level 5	This level indicates fully automated driving. Therefore, the operator is excluded from the operation or control of the vehicle.

The ultimate goal of these developments is for mobile robots to achieve full autonomy. In addition to covering these advancements, this paper also comprehensively discusses the significant challenges faced by mobile robots and autonomous vehicles, providing insights into the obstacles that must be overcome to realize their full potential. This paper is organized as follows: Section 1 introduces mobile robots, including their classification. Section 2 presents a review of the literature, referring to advances in mobile robot technology. Section 3 extensively discusses automatic parking, path following, visual-based control systems, and multibody vehicle control. Section 4 discusses the important challenges associated with mobile robots and autonomous vehicle control and proposes future research directions. Section 5 concludes the aforementioned subject.

2. Literature Review

The advancements in mobile robot technology and autonomous vehicle control have stimulated several studies aimed at exploring new technological trends and addressing some vital challenges associated with them. Figure 2 provides a visual overview of the number of research articles published in this field between the years 2010 and 2024 as found in the Scopus database. As shown in Figure 2, the rate of publication of articles in this research space has been progressive with marginal decreases recorded in between.

An extension of these data in Figure 3 presents the Top 10 contributors. Interestingly, these data provide insight into the popularity of mobile robotics in several nations.

As shown in Figure 4, visualization of the keywords was performed using the VOSviewer software. The large clusters denote dominant themes in the mobile robot research space. Furthermore, all less frequent keywords are linked to the dominant theme (mobile robots). By analyzing this landscape, a review of the literature was performed to obtain insights into key areas. The organization of the literature review is illustrated in Figure 5.

This review organized related works based on the approach employed, targeted problems, and performance to identify the challenges and prospects in the field of mobile robots and autonomous vehicle control.

Real-time capability. In the architectural development of mobile robots, the achievement of a certain degree of autonomy (whether partial or full) implies that mobile robots must be able to perform predefined tasks in real time. Thus, any robot unable to accomplish tasks in real time is highly likely to fail and be replaced by those capable of real-time tasks. Realizing real-time capability requires the use of powerful hardware-embedded devices, especially microcontrollers [53–55], microprocessors, and computers with real-time OSs, such as FreeRTOS, QNX Neutrino, VxWorks, and other real-time ROS [56, 57]. The hardware control unit and software OS aim to ensure efficient service provision (i.e., multitasking, prioritization of tasks, preemption, inter-task communication, reducing latency, and priority inheritance), resource management, and recording keeping of all activities. Gobhinath *et al*. [58] proposed a simultaneous localization and mapping (SLAM) for mobile robots using the ROS. In this work, the ROS, which serves as an open-source Linux-supported OS and middleware, was employed in the collection and translation of the light detection and ranging (LiDAR) sensor data to facilitate effective path planning, navigation, and mapping of unknown terrains, thereby improving the operational awareness of the proposed system. To achieve real-time control of a nonholonomic or omnidirectional mobile robot, Ribiero *et al*. [59] proposed a microprocessed system that obtains important data from mobile robots via a cascaded control strategy.

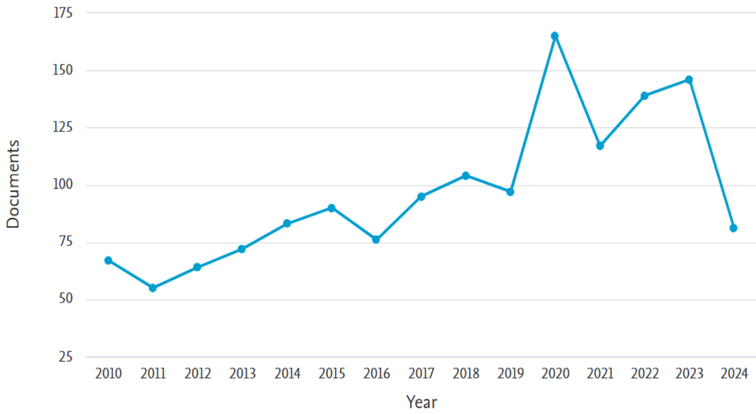

Figure 2. Published Research Papers in the Domain of Mobile Robots and Autonomous Vehicle Control

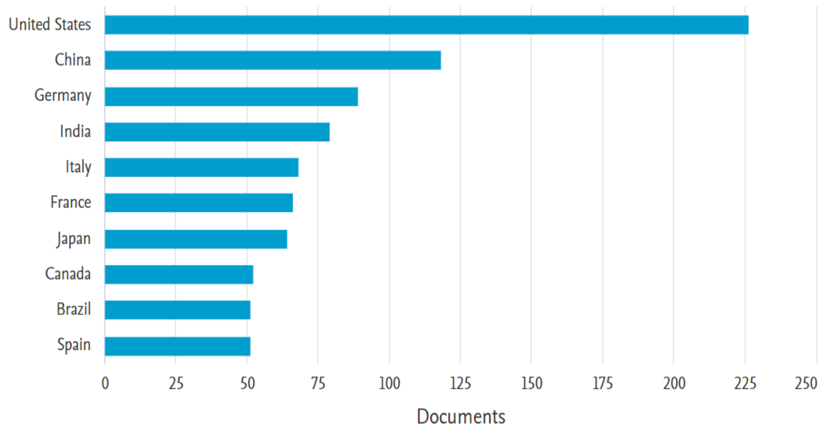

Figure 3. Country-Specific Publications on Mobile Robots and Autonomous Vehicle Control between 2010 and 2024

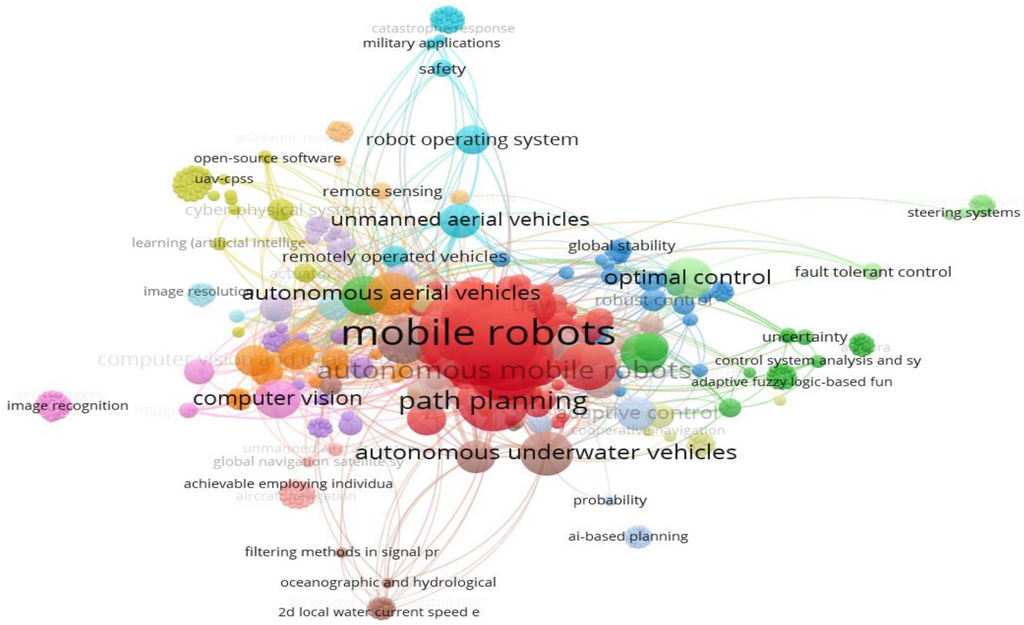

Figure 4. Representation of Keywords in the Publications on Mobile Robots and Autonomous Vehicle Control between 2010 and 2024

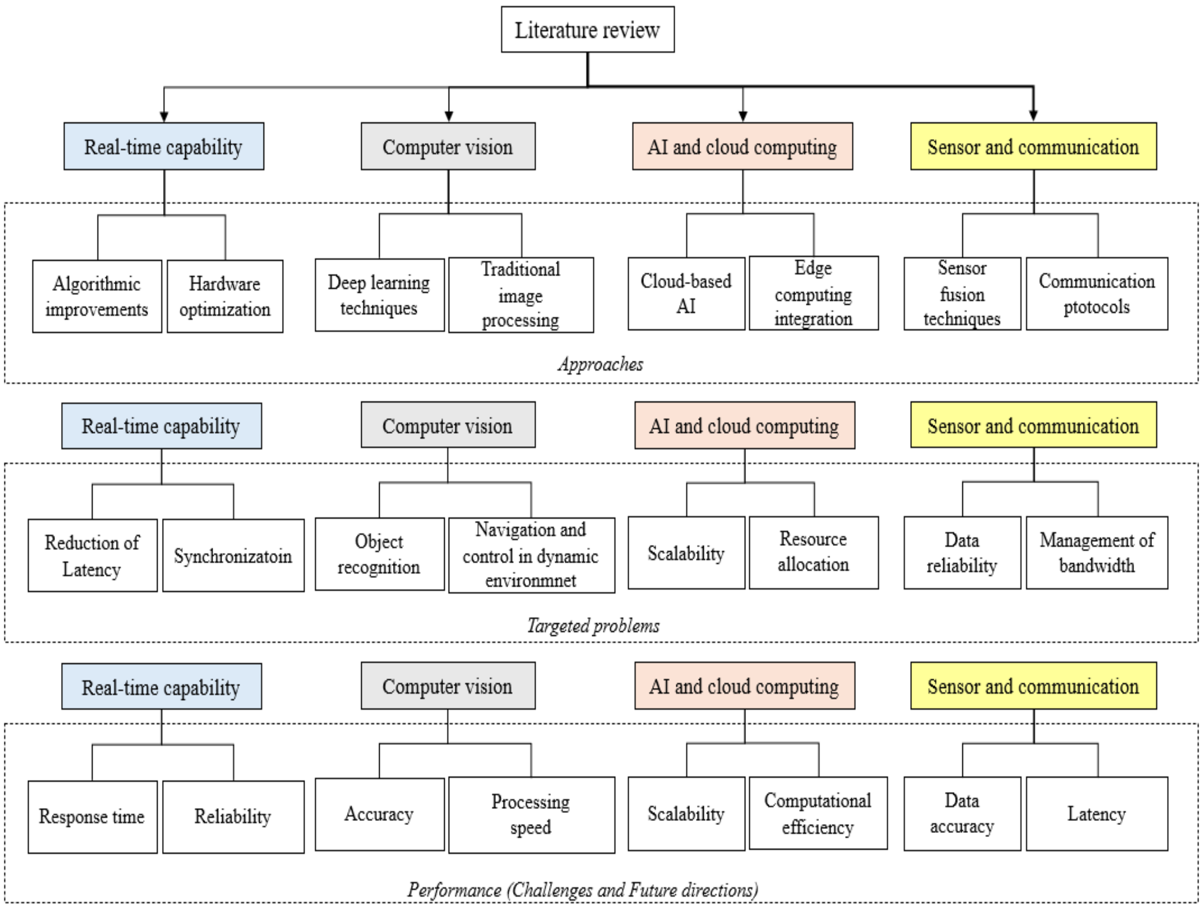

Figure 5. Organization of the Literature Review

In addition, a Lazarus integrated development environment, which is run on a Linux OS on a personal computer, enabled the supervision of the entire system development. Owing to the challenges faced by mobile robots in navigating unfamiliar environments, Boltov *et al*. [60] performed an experiment on the feasibility of real-time OSs on a Raspberry Pi microcontroller board with regard to realizing image recognition and vision-based navigation for minute self-controlled mobile robots. The proposed system employed a BCM2836 quad-core ARM Cortex-A7 processor with a dual-core VideoCore IV GPU. PREEMPT_RT and Xenomai, which are renowned real-time Linux kernel patches, were analyzed. Upon evaluation, the PREEMPT_RT kernel patch was recommended over Xenomai because of the fewer cyclic delays and higher recognition rate. Therefore, the choice of real-time OS employed in designing mobile robots needs to have a significant impact on certain important performance parameters, such as processor response time, utilization, and real-time jitters. In reference [61], a Xenomai-based architecture was developed to control a differential drive mobile robot. This software architecture was integrated with an updated version of EtherCAT Master and IgH EtherCAT open-source protocol to facilitate the deterministic exchange of information with the servo drives. A timing analysis was performed to verify the real-time response of the developed system. Based on the evaluations obtained, minimal jitter was recorded using this proposed software architecture and the execution time was acceptable in reference to other similar conducted works. Therefore, in relation to the discussed literature, the type of predefined task to be undertaken indicates the type of processing unit (CPU/GPU) and OS to use, which translates into the overall computation time and cost efficiency of the mobile robot.

Computer vision. Computer vision for mobile robots has evolved over the years, mainly attributed to the advancements in imaging technologies. To achieve full autonomy, mobile robots must be equipped with a reliable vision system to enable effective navigation and control with increased accuracy in path planning. Chae *et al*. [62] proposed a keyframe-based autonomous visual–inertial navigation system called KAVIN that performs path planning and localization using a stereo camera mounted on the sensor module of the system. The KAVIN system incorporated three essential nodes to extract image features and achieve SLAM and motion control. Because the perception of the external environment is vital, Fernández-Caballero *et al*. [63] employed a thermal infrared video camera mounted on the mobile robot to capture and detect humans in real time. A subtraction-based method and an optical flow algorithm were applied to the captured static and dynamic images, respectively. Through the alignment and analysis of the recorded images, human motion in an indoor environment was detected. To achieve effective localization of mobile robots using classifiers with rejection options, Marinho *et al*. [64] presented a study that compared different image feature extraction and machine learning methods to determine localization in an indoor environment. In their study, conventional GoPro and omnidirectional cameras were used to evaluate the system and compare the outcome to a navigation system, respectively. The accuracy and computation time were significantly improved with a Bayesian classifier for spatial movements, hence providing a cost-effective approach. Another study reported in reference [65] summarized several computer vision techniques applied to enable the localization of mobile robots. This summary included categorization based on environment, method, sensor type, and platform. In an indoor environment, da Silva *et al*. [66] proposed the localization of mobile robots via RGB-D Kinect sensors using the transfer learning technique. The sensor images taken by the mobile robot were modified into mosaic images and applied to an effective convolutional neural network (CNN) to estimate the current location of the mobile robot. According to the authors, this approach produced a model accuracy of 100% with no false positives or negatives recorded and was comparable to other computer-vision-based systems in terms of computation time. Similarly, Gamallo *et al*. [67] conducted the indoor localization of a mobile robot by employing an omnidirectional camera with a fisheye lens using the Kullback–Leibler divergence-augmented Monte Carlo localization algorithm. Operationally, the system utilized a camera model to extract all of the relevant features in the captured omnidirectional image to localize the mobile robot in real time. The use of feature-based mapping of the landscape facilitated the adaptability, scalability, and validity of the proposed model to occlusion and environmental changes. A similar approach was used in reference [68] but with a different algorithm enabling the localization of a mobile robot in a vast industrial setting using cameras with fisheye lenses. An alternative system for a hand-controlled mobile robot that was proposed in reference [69] amalgamated monocular vision with a CNN to navigate independently in the absence of maps and environmental data. The images captured by an economical RGB-D camera provided data on which the CNN model was trained and validated. According to the authors, the proposed model provided a 77% model accuracy, which enabled the mobile robot to navigate through an unknown indoor environment without maps using a low-cost stereo camera. Because most computer-vision-based algorithms employ cameras capable of detecting artificial features, such as augmented reality codes, Coelho *et al*. [70] and Baatar *et al*. [71] presented an extended Kalman filter (EKF) algorithm to localize mobile robots using this approach. They achieved the localization of mobile robots by fusing computer vision data and odometry informa-tion using the proposed EKF algorithm to realize, navigate, and estimate their position in a simulated environment. According to Coelho *et al*. [70], this approach was economical but requires practical implementation to verify its performance in the real world.

AI and cloud computing. In the bid to achieve full autonomy with regard to mobile robots, a learning mechanism that could enable mobile robots to compute quickly and make the right decisions with enhanced perception and cognitive capabilities is essential. Sun *et al*. [72] extensively discussed both model and model-free reinforcement learning as applied to motion planning systems in mobile robots. Based on their comparative analysis, model-based reinforcement learning, which employs supervised learning, exhibits higher sample efficiency, requires less data, and converges faster in terms of speed than model-free reinforcement learning. By contrast, model-free reinforcement learning needs extensive training, which limits its application. In reference [73], model-based reinforcement learning took precedence over model-free reinforcement learning when employed to provide real-life solutions to a UAV flight control problem. A combination of both model-based and model-free reinforcement learning was utilized to derive a hierarchical Gaussian process (GP) model in reference [74]. This model was used on a biped mobile robot to balance or control its motion on a rotating platform. According to the authors' evaluation, the challenge of limited training data and the issues of model overfit were surmounted using this stratified GP model. Because of the undesirable problems and demerits associated with operating indi-vidual mobile robots in complex environ-mental settings, mobile robots need to collectively perform tasks in a shared workspace [75]. In reference to this, centralized and distributed reinforcement learning algorithms were applied in references [76] and [77, 78], respectively, to enable multi-mobile robot cooperation and path planning. However, despite the benefits, there exist resource constraints and computational complexity for large-scale mobile robots.

Table 2. Summary of Current Technologies and Their Associated Challenges

Reference	Domain	Task	Processing Unit	Operating System	Challenges
[99, 100]	Real-time capability	Navigation	Real-time capable GPUs and high-performance CPUs	RTOS (UNIX and ROS 2 FOXY)	Ensuring low-latency response and maintaining deterministic behavior
[101, 102]	Real-time capability	Obstacle avoidance	NVIDIA Jetson, ARM Cortex-A series	RTOS (preemptive and non-preemptive RT)	Balancing power consumption with performance
[103, 104]	Computer vision	Object recognition	GPUs (NVIDIA, GeForce, and Tesla)	Ubuntu with CUDA	Handling large volumes of data while achieving real-time inference
[105, 106]	Computer vision	Scene comprehension	TPUs, Intel Movidius	Linux	Processing under adverse conditions
[107, 108]	AI and cloud computing	ML and model deployment	GPUs, CPUs, TPUs, and FPGAs	Windows with CUDA, Ubuntu, and TensorFlow Lite	Network latency and real-time model updates
[109, 110]	AI and cloud computing	Data analytics	Multicore CPUs, server-grade processors	Cloud-based OS (AWS Greengrass)	Computational data management and privacy
[111, 112]	Sensor and communication	Sensor fusion	DSPs, ARM Cortex-M series	Embedded Linux and FreeRTOS	Managing bandwidths and synchronizing multiple sensor inputs
[113, 114]	Sensor and communication	Cloud-based or edge-based device communication	Low-power microcontroller	Lightweight OS (RIOT and Zephyr)	Securing data transmission with minimum latency

To identify faults in the roller bearings of a smart mobile robot, Xian [79] employed an algorithm with the parallel combination of empirical mode decomposition (EMD) and support vector machine (SVM) on the Spark cloud computing framework. According to a comparative assessment of the parallel EMD-SVM algorithm, a mean F_1 score of 97.9% was recorded, which surpassed the performance of a serial EMD-SVM algorithm with regard to accurately identifying and classifying faulty vibration signals in the roller bearings of the mobile robot. Path planning for multi-mobile robot cooperation was realized in reference [80] with cloud computing. The proposed system utilized laser scanners, an optimal reciprocal collision avoidance algorithm, and cloud servers to detect, compute, and provide real-time information required by the multi-mobile robots to enable effective cooperation and navigation in unorganized settings without collision. As indicated by the authors, this system remained collision-free irrespective of the sudden orientation of obstacles in the workspace. Thus, offloading enormous tasks to cloud-based and edge-based computing systems for intensive processing of data facilitates operational reliabilities in mobile robots [81, 82].

Sensor and communication. The perception and processing of the external environment and the internal conditions by mobile robots are extremely vital for accurate mapping, navigation, and localization. To enhance the performance of mobile robots, several sensor fusion techniques have been adopted [83–85]. In relation to this, Haider *et al*. [86] proposed a navigation system that employed a hybrid adaptive neuro-fuzzy inference system (ANFIS) and global positioning system. At the center of the operation of this system, three ultrasonic sensors were used to obtain measurements of obstacle distances relative to the mobile robot. Afterward, these data are inputted into the ANFIS module at a specified time interval to enable navigation in an uncharted and unorganized environment. An efficacy of 20% was determined when evaluated and compared with current systems. Tran *et al*. [87] incorporated a combination of two-dimensional (2D) LiDAR and three-dimensional (3D) ultrasonic sensors to provide both 2D and 3D maps to facilitate navigation, localization, planning, and obstacle avoidance in real time using data-level, feature-level, and decision-level sensor fusion techniques. According to the authors, this proposed method is economical and improves the perception of mobile robots in both dimensional planes. In reference [88], a 2D laser scanner was fused with an inertial measurement unit (IMU) to enable the localization of mobile robots. To achieve the localization of mobile robots, a recurrent CNN architecture was employed to estimate the poses of mobile robots by utilizing the sequence data obtained from the laser scanner and the IMU. Based on a comparative analysis with conventional methods, from the authors' perspective, this method is effective in cases where mobile robots move with large angular velocity. In the quest to improve the accuracy of SLAM, Du *et al*. [89] presented an EKF-SLAM approach, which utilized LiDAR and a bio-inspired polarized skylight sensor (PSS) to acquire the orientation and position of mobile robots. This multisensor fusion technique resulted in the reduction of the localization and mapping errors by 30% and 25%, respectively, when compared with other multisensor fusion techniques without PSS utilization. Thus, their proposed approach applies to outdoor mobile robot navigation. Other sensor fusion methods have been applied to fault detection in mobile robots and with fault-tolerant schemes proposed in this regard [90, 91]. Cooperation and coordination among mobile robots require the establishment of an effective medium of communication that enables the transfer of information without delay (high throughput with low latency). Thus, a variety of network infrastructures or architectures ultimately have a significant contribution in this regard. Haxhibeqiri *et al*. [92] proposed a high-level wireless fidelity architecture, which was flexible, configurable, and capable of operating in infrastructure networks and ad hoc modes. To surmount the challenges of using solely infrastructure networks, the proposed architecture inherently possessed mesh capability to solve both detection and coverage issues as a result of shielding effects. Based on the experimental evaluation of the proposed architecture, the broadcast scalability was analyzed, other vital parameters were validated, and the results were benchmarked. This architecture was mainly developed for indoor industrial applications for autonomous guided vehicles (AGVs). Ultrahigh-frequency radio frequency identification (UHF-RFID) communication was employed in reference [93] to track a dynamically targeted object. In this approach, a mobile robot was provided with a UHF-RFID reader to track a dynamically targeted object that has been equipped with a passive UHF-RFID tag. Through a developed cost function, the distance and bearings of the tag (on the dynamically targeted object) relative to the reader (on the mobile robot) were computed in real time with a proportional–integral–derivative (PID) algorithm. Imperatively, the type and range of communication play a critical role in the formation control of mobile robots [94–96]. As a result of the differences in operational environments, AUVs mostly operate using underwater communication sensors and devices, such as sonar, hydrophones, modems, and other acoustic beacons, to aid in navigation and localization [97]. Hence, efficient wireless sensor networks and processing methods can enhance the communication and operational capabilities of mobile robots [98].

3. Autonomous (Self) Driving

Ground-operated mobile robots, including all of the legged and wheeled AGVs or UGVs, are statistically the predominant class of mobile robots existing in the physical environment [115]. Because of the vast interactive capabilities of this class of mobile robots with humans, the concept of achieving full autonomy is realistic. Current implementational successes are in the areas of automatic parking, path planning and following, visual-based control systems, and multibody vehicle control.

Automatic parking. In reference to WMRs, automatic parking involves autonomously navigating and parking in designated spaces with no human interventions. Thus, achieving this objective requires the use of the reviewed concepts of real-time capabilities and the adoption of computer vision, AI and cloud computing, and sensor and communication. In automatic parking, sensors are needed to perceive the environment by detecting obstacles in real time and processing the sampled information to localize its position and find the optimal path to the parking space [116]. With the revolution in Industry 4.0, the advancements in technology have significantly impacted the growth rate of mobile robots globally, especially in logistics warehouses. In Figure 6, a typical case study of the production of AGVs is presented.

The idea of automatic parking emerged because of the increasing trend in the production of autonomous ground or guided vehicles. That is, with the increasing production rate, the challenge of automatic vehicle parking is projected to increase proportionally because the computational complexity and occurrence rate of deadlocks also increase simultaneously [117]. Thus, automatic parking is an essential block in the development of UGVs or AGVs. Automatic parking systems for AGVs are designed to operate by carefully navigating to the target or designated position using a feasible, short, and obstacle-free path at a specified guided rate and avoid deadlocks via an algorithmic control process [118, 119]. The automatic parking systems must interact with the immediate environment to collect exteroceptive infor-mation using sensor-fusion-based models [120–122]. Through this process, the relevant information is passed to the path planning unit for the creation of the best-suited route to navigate, as depicted in Figure 7.

Path planning. How well an automatic parking system performs is essentially dependent on the adopted path-planning approach. Therefore, path planning is a critical decision-making stage that requires the use of algorithms to operate on vital, either static or dynamic, data. Conventional algorithms encapsulate sampling [123, 124], graphs [125, 126], and data-based algorithms [127, 128]. Bionic-based and learning-based algorithms are currently utilized in motion path planning for numerous mobile robots to identify the optimal path in unchartered and unstructured environments [129, 130]. An overview of selected path planning methods is presented in Table 3 based on the algorithm employed.

Visual-based control systems. Visual perception of the real environment is indisputably significant in achieving autonomous operation because it provides extensive data. For instance, to complete successful path following or tracking, an efficient visual-based control mechanism for mobile robots needs to be established. Thus, convergence and the capability to follow a spatial path at a desired velocity require vision to complement and execute autonomous operations. Visual-based control systems for mobile robots essentially comprise an input sensory device, an algorithmic processing unit, and a control theory. The input sensory devices are predominantly application-specific cameras, as shown in Figure 8. 3D depth cameras, such as RGB-D cameras [141], RealSense series binocular cameras [142], and Kinect cameras [143], have all been employed in human detection and object tracking activities. Similarly, stereo cameras equipped with depth perception capabilities [144–146] have also been used in object detection. Other sensory devices include RGB cameras for object detection and recognition [147–149], monocular cameras [150], and eye trackers [151] for target tracking. Moreover, the microscopic or endoscopic camera cannot be overlooked because of its significant contribution, especially in the area of healthcare delivery [152, 153]. In this regard, the use of multiple cameras with other sensor fusion techniques in most cases essentially improves the performance of the mobile robots via a control feedback mechanism, established image processing algorithms, and control theories.

Image or video processing algorithms facilitate the detection or identification of targets based on captured data from the input sensory device. The choice of algorithm is dependent on the applications or functions of the mobile robot, computation time, and computational power available for use. For instance, based on the designed operation, machine learning algorithms, such as CNNs [154, 155], have been employed to perform various tasks in AGVs. Hence, the controller or processing unit required and on which these algorithms are run equally impacts the overall performance of the visual-based control systems either positively or negatively.

Multibody vehicle control. Mobile robots, including AGVs, are categorized as multibody systems or vehicles based on their capability to exhibit dynamic kinematics, such as translational and rotational motion or displacement. In reference to this, providing control for these systems is therefore key to realizing fully autonomous operations. Established on the principles of classical mechanics [156], several algorithms, such as the Newton–Euler [157], Lagrange, and Kane equations, have been applied to model, analyze, and describe the linear and nonlinear dynamics of mobile robots [158, 159]. An integral part of mobile robots and vehicle control are the controllers, which consist of a PID controller and other path-following controllers, such as the Stanley controller, optimized look-ahead distance pure pursuit algorithm, and pure pursuit controllers. Based on these developed controllers, mobile robots can perform a variety of tasks, such as speed control (cruise control), braking, and steering control (e.g., Ackerman, differential, and independent steering wheels) to achieve efficient navigation and tracking [160–162].

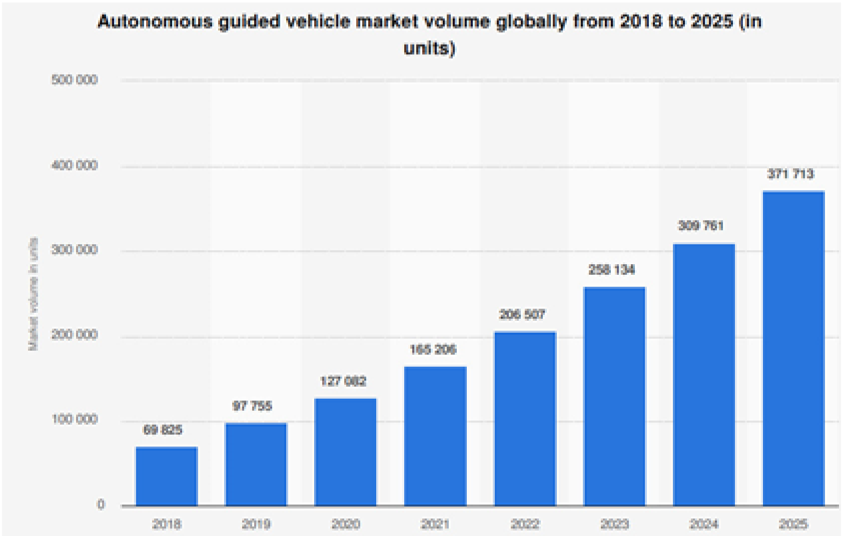

Figure 6. Current Global Autonomous Guided Vehicle (AGV) Market Volume and Prediction between 2018 and 2025 [115]

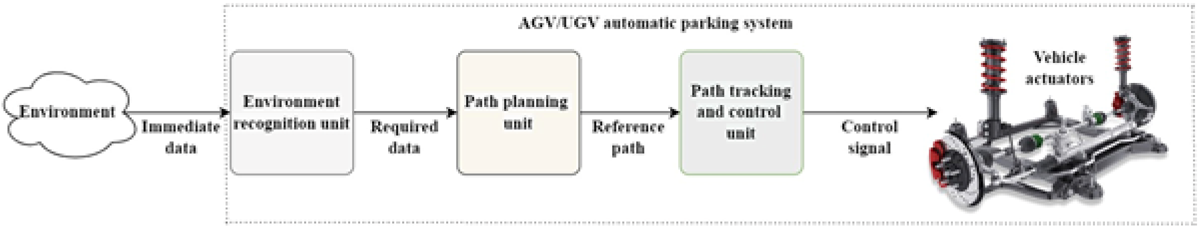

Figure 7. Systemic Overview of the Parking Systems for AGVs

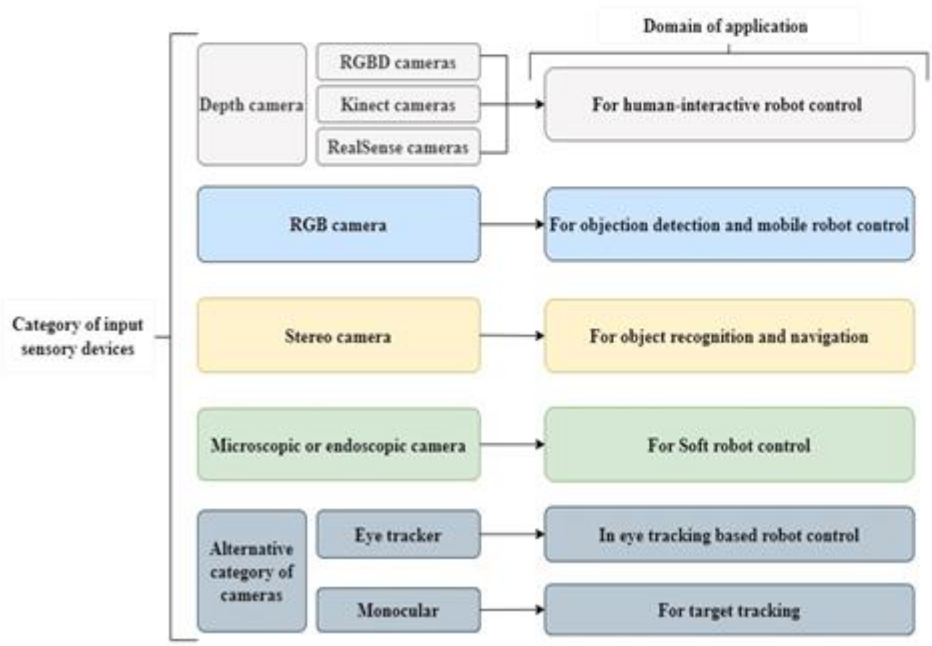

Figure 8. Category of Input Sensory Devices and Domain Of Application

Table 3. An Overview of Path Planning Approaches

Authors	Algorithm	Class of Algorithm	Overview
[131]	Deep Q network deep reinforcement learning (DQN-DRL)	Learning-based	Proposed a DQN method that acquired sensor data of the immediate environment and merged the current location of the robot and the designated point to create a state space. This formed the input of the network. The output of the network model is ascribed to the *Q* value at the recent location. Imperatively to enhance the operation efficiency, a ε-greedy strategy was employed for action selection.
[132]	Ant colony optimization (ACO)	Bionic-based	Presented a fallback strategy to enhance path planning in AGVs using ant colony optimization. A valuation function was employed to optimize the procedure of calculating the heuristic function. In addition, a reward or penalty technique was used for the pheromone update method. Thus, the optimal path is identified with high search efficiency.
[133]	Optimal trajectory planning and deep neural network	Learning-based	Proposed a multilayer approach that combined optimal trajectory planning and deep learning methods. A nonreactive trajectory optimization method was iteratively done to obtain a set of time-based optimal parking trajectories in the starting layer. The acquired parking trajectory dataset is subsequently given to the lower layer and the trained deep neural network performs vehicle control via a comprehended parking trajectory steering mapping relationship.
[134]	Fuzzy-based genetic algorithm	Bionic-based	The challenges of routing and motion planning applied to vehicles in a flexible manufacturing system (FMS) were presented and a proposed motion planner was merged with a scheduler. This approach allowed AGVs during navigation to update their destination resources and successfully execute the transport of products in the FMS.
[135]	Genetic algorithm and Kohnen Q-learning algorithm (GA-KL)	Learning-based	A dual-level path planning technique was proposed for multi-AVGs which incorporated a global path planning scheduling policy. A combined genetic and Kohnen learning algorithms were employed to achieve both global and local planning. Based on this approach, dynamic obstacles were avoided, and autonomous path findings were completely realized.
[136]	Dijkstra algorithm	Graph-based	Proposed an improved Dijkstra algorithm that integrated an eight-angle search technique for planning an optimized path. The optimized path was established using the Dijkstra algorithm where a grid method was employed to model the storage environment in MATLAB. Upon simulation, this process enabled efficient obstacle avoidance using a short and collision-free path with less turning angle.
[137]	Multiple heuristics rapidly exploring random tree (MH-RRT) algorithm	Sample-based	A merged multiple heuristic with a rapidly exploring random tree (MH-RRT) algorithm was proposed to enable path planning in AGVs. Based on this approach, both global and local path planning were realized via a receding horizontal planning (RHP) approach. Further integration of the algorithm with an enhanced double-step time elastic band provided an optimized, smooth, and secured path within a short period.

Table 3. *Continued*

Authors	Algorithm	Class of Algorithm	Overview
[138]	A-star (A^*) and dynamic window algorithm (DWA)	Graph-based and data-based	Proposed a hybrid improved A-star and dynamic window algorithm (DWA) to solve the challenge of path optimization and obstacle avoidance involving several path inflection points during inspection in a complex workspace. A motion control scheme was presented based on the kinematic analysis of the inspected AGV robot and an environment map was constructed. In addition, via a 16-directional neighborhood search approach and the integrated DWA, temporary obstacle avoidance was achieved.
[139]	W-theta-star algorithm (W-Theta*)	Graph-based	Proposed a W-Theta* algorithm to address the challenge of slow path planning faced by traditional A^* and Theta* algorithms in large operational environments. A dynamic weighting approach was introduced and the W-Theta* algorithm generated optimized discrete path points with regard to trajectory processing. This algorithm provided a faster computation via a reduced path planning time with the least turn angle in comparison with the Theta*, Dijkstra, and A^* algorithms.
[140]	Improved particle swarm optimization algorithm	Bionic-based	A proposed improved particle swarm optimization algorithm dependent on differential evolution (IPSO-IDE) was used to address the problems of low convergence accuracy and maturity in path planning involving mobile robots that employed particle swarm optimization. This was realized by both an optimized scaling and cross-probability factor. Imperatively, this enabled the algorithm to adaptively control the search accuracy and the level of mutation with less sample data or information.

4. Discussions

Implications of automatic parking. Automatic parking technology has immensely reshaped the landscape of vehicle parking and is increasingly becoming a most sought-after solution for parking operations where optimized space usage is required [163]. The relevance of this system is observed in certain areas, such as urban settings and warehouses, where efficient utilization of space is of high priority [164, 165]. In other words, autonomous vehicles equipped with automatic parking efficiently carry out parking minimizing the space required for a vehicle and in effect improving the overall capacity. Furthermore, the deployment of this technology in AGVs ensures safety by minimizing accidents caused by human errors [166]. Technically, the advanced sensor fusion and real-time control algorithms facilitate safe maneuvers under unfavorable conditions, which is preferable and more reliable than those under human control [167, 168]. Therefore, minimizing the need for human interventions in vehicle parking is economical because labor costs and operational downtimes are significantly reduced [169, 170].

Current research gaps identified. Although automatic parking systems are characteristically reliant on sensors, research on how vehicles equipped with this technology maintain their optimal performance in the event of inaccuracies in sensor data and sensor failures is limited [171]. A typical case involves performance under adverse weather conditions where sensors likely underperform [172, 173]. Thus, more research is required to handle such scenarios using redundant or fail-safe systems to address this problem. Furthermore, the scalability of automatic parking systems to more complex settings with many interacting vehicles has been a lingering issue that remains a challenge [174]. Primarily, because automatic parking systems are implemented in controlled environments, research must focus on multiple autonomous vehicle coordination rather than on single autonomous vehicle scenarios [175, 176]. The absence of standardized protocols and software employed by various automatic parking systems presents problems concerning the integration of these systems with other already existing systems, indicating that the use of proprietary systems by different manufacturers ends up limiting the flexibility and scalability of automatic parking solutions [177, 178]. An important case is the challenge of effective communication among autonomous vehicles because of interoperability issues. A comparison of the performance of selected path-planning approaches in automatic parking systems is presented and analyzed in Table 4, highlighting the important parameters considered in describing the operational efficiency of autonomous ground mobile vehicles.

In relation to the performance analysis of the simulations and experiments conducted in Refs. [179–181], obstacle avoidance and the shortest path and elapsed time were realized for mobile robots. However, currently, some important constraints generally affect the operational performance of mobile robots. The reliance on fault-tolerant sensor fusion techniques improves operational performance. Nonetheless, the challenges of delay in real-time feedback, inadequate sampling efficiency, low accuracy, and the absence of external environmental information remain. In addition, changes in the external environment (e.g., humidity, temperature, and light) immensely affect the perception, recognition, observation, navigation, and tracking capabilities of autonomous mobile robots [182, 183]. The constraints of power management are also a significant challenge with regard to the operation of mobile robots. Prompted by several studies, predictive monitoring systems for power management using the Internet of Things technology have been developed to ensure battery efficiency [184]. Recent advancements in battery technology have provided improved battery storage capacity using lithium materials [185]. Although this technology has been beneficial, a more reliable, cost-efficient, and permanent battery is required to make automatic parking systems more energy-efficient. Furthermore, despite the progress made in state-of-the-art battery technology, providing wireless power transfer solutions for mobile robots remains a hurdle to surmount [186].

Future research areas. Considering all of the current technologies underlining mobile robot operations and autonomous vehicle control, future works must further explore the following fields:

Sensor fusion. Presently, mobile robots equipped with automatic parking rely heavily on data from a variety of sensors, such as cameras, LIDAR, ultrasonic sensors, and IMUs [187, 188]. However, each of these sensors has its merits and demerits, which can be further worsened by external environmental conditions. In this regard, future research should be conducted to develop efficient deep learning algorithms that integrate multimodal data fusion with AI to dynamically weigh sensor inputs to achieve reliable operation [189]. In addition, building redundancies or fail-safes into sensor systems should be explored to mitigate data inaccuracies [190]. Moreover, emerging trends in quantum sensors should prioritize integration with already established fusion frameworks [191].

Collaborative multi-vehicle parking. Following the increasing number of mobile robots and autonomous vehicles, research into decentralized algorithms for efficient collaboration with multiple robots or vehicles should be considered, fundamentally enabling mobile robots or autonomous vehicles to make independent decisions while considering the actions and positions of surrounding robots or vehicles [192]. Hence, standardized communication protocols must exist to enable information sharing in real time [193].

Human–robot interaction. Human–machine interaction has been in existence for some time. Nonetheless, users need to communicate and trust the feedback response from mobile robots and autonomous vehicles. Therefore, future research should delve deeper into providing explainable features via user-friendly interfaces and AI models to increase the level of trust, which can be boosted by developing evaluation frameworks [194, 195].

Energy efficiency and sustainability. The progression toward the optimal use of energy and its subsequent implication of reducing carbon footprints in the environment is a growing need. In reference to this, energy efficiency is possible for battery-powered robots or autonomous vehicles adopting energy-aware path planning [196].

Table 4. Performance of Path Planning in Autonomous Guided Vehicles

Parameters	[179]	[180]	[181]
Distance of the shortest path	521 pixels	387 cm	914 m
Obstacle avoidance	Yes	Yes	Yes
Elapse time	8.75 s	6.23 s	1.08 s
Type of algorithm	Genetic (GA)	Hybrid swarm optimization (ACPSO)	Improved rapidly random tree (RRT)
Type of mobile robot	AGV	AGV	AGV
Test of simulation	Yes	Yes	Yes

Thus, future researchers should or must develop algorithms that not only focus on obtaining the shortest path but also consider the most energy-efficient path [197], which involves balancing the vehicle speed with its power consumption (e.g., taking routes with less need for complex maneuvers). Moreover, adopting futuristic low-power hardware components, such as sensors, microcontrollers or processors, and actuators, is extremely important to energy efficiency [198]. In other words, the use of energy-harvesting technologies should be considered in the design process of mobile robots and autonomous vehicles [199]. Thus, addressing the issue of sustainable energy would require that future directions be geared toward integrating renewable energy sources, especially for outdoor mobile robots, including autonomous vehicles. Therefore, priority should not only be given to the domain of energy generation but also to efficient energy storage and management systems [200–202].

5. Conclusions

This paper presents an extensive review of relevant aspects of mobile robot technology where substantial improvements have been made and are presently ongoing to address the aforementioned challenges. Based on the discussed points, mobile robots have become an indispensable machine that is beneficial in nearly all fields of human endeavors. Thus, realizing completely autonomous operations in complex environments and conditions indicates that mobile robots must be equipped with the requisite mechanisms that would enable them to adapt adequately and self-learn. Hence, to achieve this, future works must incorporate AI and machine learning into mobile robots, adopt collaborative systems for multiple robot operation, improve human–robot interaction, and achieve all of these in real time with efficient use of energy.

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