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Review

Automated guided vehicles and autonomous mobile robots for recognition and tracking in civil engineering

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ABSTRACT

Automated guided vehicles (AGVs) and autonomous mobile robots (AMRs) have been widely used recently to solve various engineering problems in logistics, manufacturing, and high-risk labor. This paper reviews the latest research on AGVs and AMRs and includes results from different past and present research areas on AGVs and AMRs. In addition, various navigation principles of AGV are compared. This paper also discusses and compares various types of AGV/AMR visual tracking control technologies and presents three recognition and tracking integration technologies, which improve the accuracy, robustness, and real-time performance of AGV/AMR visual navigation systems. Finally, the application of AGV/AMR technologies in civil engineering is reviewed and discussed, including for road pavements, bridges, and construction. These technologies play an important role in construction, defect detection, and condition inspection, free up manpower and improve the degree of automation in the civil engineering industry.

1. Introduction

AGVs were originally used to transport goods in place of tractor-trailers and drivers, and were gradually used in the warehousing and logistics industry. AGVs rely on tracks or predefined routes and usually require operator supervision. AMRs are an evolution of AGVs. They are robots which have the ability to understand and move independently in their environment. AGVs and AMRs have been used in the field of civil engineering in recent years.

According to the definition of the American Material Handling Association [1], an AGV is controlled by an industrial computer and follows a predetermined path autonomously. It can avoid obstacles autonomously, and can complete a series of handling tasks to transport goods to designated locations. It is based on a wheel-driven mobile robot [2]. AGVs have three main operations and features: (1) materials handling. (2) replacement of manual work. (3) mobile workbench. The application of AGVs has four advantages: (1) Reduction of the occurrence of accidents related to trolleys in the process of cargo loading and unloading. (2) Reduction of labor in product loading and unloading, handling, and other links. (3) Tracking of goods and reduction of their rate of loss. (4) Reduction of pollution and power consumption [3]. Based on the above advantages, the AGVs shown in Fig. 1 are widely used in storage, manufacturing, medicine, power inspection, and other fields.

In recent years, AMRs have been able to navigate without physical or electromechanical guidance devices, making them promising and practical. This has also brought opportunities for the development of civil engineering. Typically, AMRs have been developed to be widely integrated and used in factories, military operations (such as unmanned ground reconnaissance vehicles), healthcare (such as drug delivery and assistance with the movement of disabled patients), and households (such as floor cleaning and mowing) [8]. AMRs are generally regarded as mobile robots (such as non-remote-control drones, driverless vehicles, etc.) with strong autonomy (they can make a reasonable, accurate and timely response to various dynamic changes in the environment), which can automatically navigate from one place to another for the completion of specific tasks. Conventionally, an AMR is designed to move according to a predefined path in indoor or outdoor environments. For indoor

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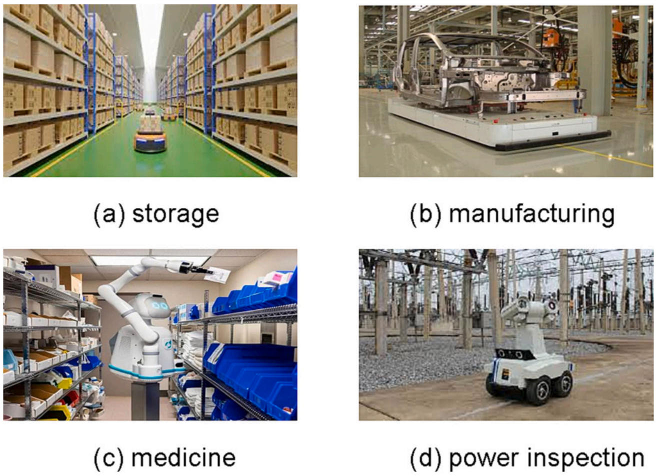


Fig. 1. Applications of AGV in different fields [4–7].

navigation, mobile robots are based on floor plans and inertial measurement units (IMU). Typically, for an AMR to perform its tasks, it must have a series of smart environmental sensors. These sensors are installed on the robot or as external sensors at certain locations in a dynamic environment (high speed train, instrument landing sensors for civilian and military air operations). The different types of sensors installed on mobile robots make the design of the entire system very demanding [9,10]. The basic knowledge of mobile robots includes movement, perception, and navigation.

This article reviews the progress of AGV/AMR technology and their industrial applications in recent years. Our review section also presents important timetables, milestone flow charts, implementation examples, and relevant images, and outlines key advances in AGV/AMR research and application in recent years, from concept to application. Table 1 and Table 2 summarize comparisons of existing AGV and AMR studies, respectively. Table 3 shows technical comparisons of AGVs and AMRs. It is worth noting that existing publications on AGVs and AMRs do not provide any in-depth discussion on how to apply the findings to the field of civil engineering.

Therefore, a review article is provided to discuss past AGV/AMR research results, and reveals that existing methods can utilize AGV/AMR technology to provide better solutions to problems in the field of civil engineering and improve the automation and intelligence levels of civil engineering. The remainder of this article is organized as follows. The second section reviews recent AGV and AMR studies and summarizes their contributions. Important advances in AGV and AMR research, as well as timeline flow charts and graphical descriptions of factory implementations, are presented. In the third part, the principles of AGV and AMR navigation are presented and compared, and the visual navigation tracking technology is considered. The fourth part explains the integrated technology of identification and tracking based on AGV or AMR technology. The fifth part focuses on a review and discussion of the application of AGV and AMR technology in the field of civil engineering. The sixth part discusses the existing challenges and research prospects in civil engineering. The conclusions are presented in the seventh part.

Table 1
Summary of existing survey articles on AGVs and their contributions.

Application field	Contributions
Localization, Navigation	Using Ultra Wide Band(UWB) for robot localization on AGVs [11–15].
	AGV localizing with sensor fusion [16–20].
	Lidar-based navigation on AGVs [21–23].
	Vision-based navigation on AGVs [24–26].
Scheduling, Path-planning	AGV fleet scheduling [27–31].
	The case for optimized path-planning for AGVs [32–35].
Practical applications	Warehousing and logistics [36–39].
	Industry [40,41].
	Agriculture [42].

Table 2
Summary of existing survey articles on AMRs and their contributions.

Application field	Contributions
Locomotion	Locomotion mechanism of wheeled robot [43–46].
Perception	Survey of robot-to-robot perception, active perception framework, hybrid multi-sensor fusion, deep learning, wheeled mobile robot currently in use on AMR locomotion [47,48].
Navigation	Survey of Lidar, RGB-D camera, deep reinforcement learning, adaptive neuro-fuzzy inference system, neural network in use on AMR navigation [49–53].

Table 3
Technology comparisons of AGV and AMR.

	AGV	Lidar AMR	Visual AMR
Localization	Magnetic bar, QR code	Reflective strips, Lidar SLAM	Visual SLAM, Visual semantic localization, Multimodal fusion
Navigation	Fixed route	Free navigation	Free navigation
Avoidance	Stop and wait to avoid obstacles	Lidar obstacle avoidance	Multimodal fusion, Visual obstacle avoidance
Features	No intelligence	1.Can only be positioned in a stable environment. 2.The obstacle category cannot be distinguished, and the tracking and trajectory prediction cannot be done well. 3.Unable to achieve stable following and visual interaction	1.Can locate in complex dynamic environments. 2.Can distinguish obstacle categories and make good tracking and trajectory prediction. 3.Stable following, capable of visual interaction, high tolerance to the environment.
Cost	Magnetic strips, QR codes, etc. require regular maintenance and update	The cost of lidar, and later replacement and maintenance	Low cost of camera, low maintenance cost for later replacement

2. Development of AGVs and AMRs

In past decades, researchers have sought to optimize logistics and industrial processes. Since Barrett Electronics of Northbrook, Illinois, USA, introduced the first known AGV in 1953, AGVs have been integrated into warehousing and logistics activities, using track-guided magnetic systems, optical sensors, and color bars as guidance technologies [2].

The integration of artificial intelligence (AI) technology and the use of open-source software are also common, such as in the robot operating system (ROS) [54,55]. The flowchart in Table 4 shows the complete development schedules and AGV examples emphasizing the integration of the various technologies referred to above. They are important achievements in AGV research and integration over the decades since the birth of AGV technology.

The first patent on AMRs was issued in 1987 [63]. Before that time, researchers had been studying systems which were not fully autonomous, but this was the predecessor of AMRs. A complete flow chart of relevant AMR research is shown in Table 5. Since the 1980s, automatic radars which can navigate in dynamic environments have been developed. The accompanying technology includes the use of sensor-based navigation; proportional integral (PI) and fuzzy control methods have also been widely used. PI forms a control deviation according to the

Table 4
Timetable for AGV development and research work.

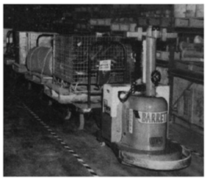
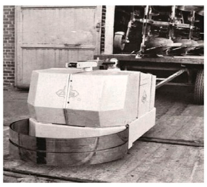
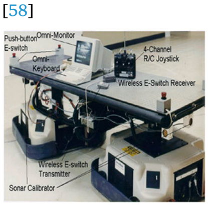
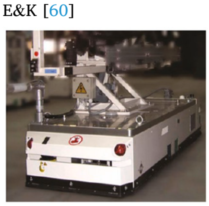
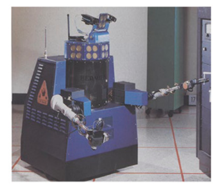
Years	Products	Accomplishments
1950s	 The first AGV (Guide-O-Matic) [56]	Some vehicles use optical sensors to track colored bars on the floor. Others follow the induced magnetic field produced by conductive strips embedded in the factory floor.
1960s	 Ameise/Teletrak with trailers [2]	Single electrical and magnetic sensor systems are installed in cargo commissioning in the food industry. Vehicles drive from station to station along a predetermined path and stop at stop signs when they recognize a target.
1970s	 Volkswagen (Germany) [57]	AGVs with onboard computer and control cabinet. Active induction track guidance with wires in the floor is widely used.
1980s	 Car manufacturing with AGVs [58]	AGVs use lasers and infrared for guidance. High-performance electronic equipment and microprocessors for location recognition.
1990s	 OmniMate [59]	Omni-directional wheels and ultrasonic sensors are applied to AGVs. Ability to detect and correct unsystematic odometer errors for more reliable travel over greater distances.
2000s	 E&K [60]	Artificial intelligence widely used in navigation, collision avoidance, guidance, and AGV vision systems. Tracking based on wireless networks. Cooperative AGV deployment.
2010s	 dpm [61]	Wide use of open source software, ROS (such as Robotnik), roscpp (ROS based on c++), and rospy (based on Python). Open source AI implementation for AGVs.
2020–present	 EVO roller2 [62]	Can move in all directions, can increase productivity, the vehicle can interact at different levels with the customer's IT infrastructure is well scalable, reconfigurable, guarantees the highest level of active safety certification PL-D.

Table 5
Timeline of and research work in AMR development.

Years	Products	Accomplishments
1980s	 HERMIES-IIB [64]	Can navigate among moving obstacles using only its sonar sensors, or can navigate using vision—but only in essentially obstacle-free regions.
1990s	 HILARE II 2bis [65]	French autonomous mobile robot equipped with ultrasonic sensors and laser telemetry. Can complete motion planning and control, trajectory tracking.
2000s	 Jido [66]	Microcontroller-based coordinated control of mobile robotic arms. Can perform positioning, navigation, obstacle avoidance, and robotic arm control.
2010s	 NRG VaultBot [67]	The VaultBot two-arm mobile manipulator and its integration with the robot operating systems MoveIt! and RViz were introduced, improving the effectiveness of system autonomy.
2020–present	 ANYmal [68]	A novel motion planner and controller are proposed that together enable ANYmal equipped with passive or powered wheels to perform hybrid motions.

given value and the actual output value, and forms a control amount by linearly combining the proportion and integral of the deviation to control the controlled object. In the past ten years, the development of AMR and AGV technology has become more interconnected, and an AMR usually has more onboard intelligence than an AGV. Our review focuses on understanding the latest research and gaps in existing AGV/AMR research knowledge:

- Localizing, scheduling, and path planning;
- Navigation, control, and guidance algorithms.

In our study, we selected large scientific resources and repositories, such as Google Scholar, IEEE Xplore, and WEB OF SCIENCE, using the selection criteria listed in Table 6 [69,70]. In recent years, most research work on AGV/AMR integration and its deployment in academia and industry can be summarized as follows.

2.1. Localizing, scheduling, and path planning

AGV localizing includes determining the position of the AGV without prior information about its position [71]. To integrate AGV more effectively in a manufacturing environment, localization, path planning, and AGV scheduling are critical. Kim et al. [72] adopted the improved Dijkstra algorithm as an AGV path planning algorithm, and obtained the optimal solution for the task of AGVs transferring each load to the specified location along the path generated by the system. Based on genetic algorithm(GA), a method to search for the optimal solution by simulating the natural evolutionary process, the path planning problem of AMRs in wireless sensor networks was studied by Zhou et al. [73], and a system model of the automatic control system in path planning was designed using GA. The A* algorithm, which considers the position information of the target point of the mobile robot and searches along the target point, was introduced by Zhang et al. [74], and is mainly used for global searches in a static environment. However, the path planning of mobile robots has gradually become aware of environmental information and is dynamic. The D* algorithm is mainly used for the path exploration of robots. This algorithm represents the problem space as a series of states representing the robot's position and orientation [74].

Wang et al. [75] applied neural networks to help adjust the proportional integral differential (PID) gain to improve the speed adjustment of an AGV when turning or arcing. PID is a control system which controls according to the proportion, integral and differential of the error generated by comparing the information collected from the real-time data of the controlled object with the given value. Global descriptors are obtained from omnidirectional images using auto-encoders and convolutional neural networks(CNNs), which were proposed by Cebollada et al. [76]. Localization tasks in indoor environments can be solved using them76. The Dempster-Shafer algorithm was used as a data fusion tool to simulate the control and actual positioning of an AMR in agriculture by Erfani et al. [77]. The designed path was traced on the soil [77]. Weinzaepfel et al. [78] proposed a CNN-based regression strategy for the visual localization of a single RGB image captured by an AMR.

The Extended Kalman Filter(EKF) method, a simple nonlinear approximate filtering algorithm, was used to integrate the data collected by the IMU, odometry, and LiDAR in the localization of the robot, and autonomous localization based on an EKF algorithm in complex indoor environments was realized [79]. Bakshi et al. proposed a two-step algorithm for fast scheduling of AMR. The algorithm first clusters the tasks, assigning the clustering tasks to a single AMR, and then uses model-based learning techniques to schedule tasks in clusters [80]. Combining an improved dynamic window approach with q-learning, Lu et al. [81] proposed an improved method for mobile robot navigation in unknown environments, and achieved the path planning of robots in static and dynamic unknown environments.

Algorithm design and implementation for AGV and AMR positioning, scheduling, and path planning is still an ongoing field which has received extensive research attention over the past decades. The use of classical algorithms such as A* and D* leads to problems of large computation demands and low processing efficiency, respectively. Therefore, researchers have been working on hybrid algorithms and improved algorithms, such as artificial potential field algorithms and improved Dijkstra's algorithms. Kalman Filtering(KF) and EKF for AGV and AMR data fusion applications have also received extensive attention in the past decades. KF is an optimal recursive data processing algorithm. With the development of machine learning and the improvement of computing power, the utilization of high-speed computing resources may help to increase the processing speed of these classic algorithms and their variants for AGV and AMR path planning, positioning and task scheduling.

Table 6
Topics and scope of publications in this review.

Topics	Publication Scope
Articles on AGV/AMR positioning, scheduling, path planning, navigation, control, AGV/AMR design, and use case.	Articles published in IEEE Xplore, Google Scholar and WEB OF SCIENCE.

2.2. Navigation, control and guidance

Navigation, control, and guidance technology is the second major area of AGV and AMR research which has received extensive research attention. Xu et al. [82] designed an AGV-integrated navigation algorithm based on fuzzy PID adaptive KF. A 2-D LiDAR scanner based on a KF and line detection algorithm was used by Blok et al. [83] to navigate an AMR in an orchard row. Simultaneous Localization and Mapping (SLAM)-based EKF has been used for AGV navigation [84]. SLAM is mainly used to solve the positioning and map construction problems of robots when moving in unknown environments. Lai et al. [85] proposed a fuzzy adaptive robust EKF for robot trajectory tracking, and the process noise and measurement noise of AMR trajectory tracking were modeled by Student's t distribution.

The fuzzy reasoning method combined with the PID control method was applied by Silvirianti et al. [86] to realize the stability and speed control of AGV. Azizi et al. designed a nonlinear model predictive control (NMPC) strategy to stabilize a robot in the desired position and orientation. NMPC is a closed-loop optimization control strategy based on a nonlinear model. The Velocity Obstacle method was introduced into the NMPC system to avoid AMR collisions with fixed obstacles [87].

A high-precision path tracking method based on color difference threshold segmentation was proposed and used as the input of the closed-loop control method of AGV during navigation [88], and experimental results showed that path tracking accuracy was high. Karpyshev et al. [89] introduced an automatic detection and visual distress detection system for apple orchards. The system is based on neural network segmentation and detection.

Control methods and algorithms based on fuzzy reasoning, PID, NMPC, and SLAM have received extensive attention from the research community in recent years. In some cases, laser-based or vision-based systems are used with some of these algorithms and methods. AGV/AMR navigation, control and guidance problems are still largely solved by variants of classical algorithms such as PID and fuzzy inference algorithms. However, challenges remain to solve problems such as minimizing the error between expected and actual AGV/AMR trajectories and AGV/AMR motion control. Improving algorithms and configuring hardware to coordinate the operation of AGVs/AMRs while improving the accuracy and robustness of the systems remain largely unexplored.

Existing research on AGVs and AMRs is summarized in Table 7. There are still many challenges in the two broad AGV/AMR research areas. Sensors are expensive and affected by environmental factors such as signal reflection, vibration, and light intensity. The same algorithms show large performance differences between indoor and outdoor positions. Limitations of computing power cause system delays and affect real-time performance. Overcoming these challenges of AGVs/AMRs remains a challenge.

3. Navigation principles of AGVs and AMRs

The navigation technology of AGVs and AMRs is the key technology to achieve autonomy and intelligence. The navigation technology of AGVs and AMRs is diverse, and a variety of AGVs and AMRs have been developed based on multiple navigation methods [90].

Table 7
Summary of existing research work on AGVs and AMRs.

Subject	Methods	Contributions
Localizing, scheduling and path planning	Dijkstra, Genetic, A* & D* algorithms	Provides the optimal solution for the AGV's task of transferring each load to a specified location [72].
		Builds a system model of path planning based on GA [73].
		Provides path exploration for mobile robots in static and dynamic environments [74].
	Data fusion, EKF	Uses Dempster-Shafer algorithm-based data fusion to trace design paths on crop soils[77].
		Uses the EKF method to achieve autonomous localization in complex indoor environments [79].
	AI	Uses neural networks to tune PID gains [75].
		Uses auto-encoders and CNNs to obtain global descriptors from omnidirectional images to solve localization tasks [76].
	Scheduling & Path planning	Proposal of a two-step algorithm for fast scheduling of AMRs[80].
		Combination of the improved dynamic window approach with q-learning. A path planning method is proposed [81].
	Vision system	Proposes a CNN-based regression strategy for visual localization of a single RGB image captured by AMR [78].
Navigation, control and guidance algorithms	KF	Design of an integrated navigation algorithm based on adaptive Kalman Filtering [82].
		Uses 2-D LiDAR based on Kalman Filter with line detection algorithms [83].
	EKF	Combination of SLAM and EKF for AGV navigation [84].
		Process noise and measurement noise of trajectory tracking modeled using Student's t distribution [85].
	Control	Combination of fuzzy reasoning and PID control method to realize speed control of AGVs [86].
		Design of a nonlinear model predictive control strategy [87].
	Vision systems	A path tracking method based on color difference threshold segmentation is proposed [88].
		A visual detection system based on neural network segmentation and detection is proposed [89].

3.1. Fixed path navigation

Fixed path navigation is an information medium for providing guidance on the driving path, and the AGV is guided by detecting its information through sensors on the vehicle body. Its main feature is that the technology is relatively mature, but its construction is troublesome and it is relatively difficult to change the running lines of trolleys.

The basic working principle of electromagnetic navigation [91] is to bury metal wires in the driving path of AGVs or AMRs, and load low-frequency and low-voltage currents to generate a magnetic field around the wires. The induction coil on the AGV or AMR recognizes and tracks the strength of the navigation magnetic field. This achieves the navigation of AGVs and AMRs.

The optical navigation method [92] involves laying a continuous belt made of luminescent material on the ground, or the application of luminescent paint on the specified running route, and the installation of two infrared sensors to detect reflected light symmetrically on the bottom of the AGV/AMR, to enable control by deviation measurement. The driving and steering motors achieve the purpose of adjusting the forward direction of the AGV or AMR.

Tape navigation [93] uses a magnetic guide belt laid on the ground and a magnetic induction navigation sensor. The relative one-dimensional coordinate signal of the magnetic induction sensor and the magnetic guide belt are obtained, and the coordinate signal is transmitted to the controller, and the controller controls the vehicle to follow the magnetic guide belt according to the signal state.

3.2. Free route navigation

Free path navigation can plan guidance paths and guide AGV movements in real time, as required. The manufacturing cost is high, but the change of the running line of the trolley is very easy and the system has high flexibility.

The basic working principle of the inertial navigation [94,95] method is to install a gyroscope on the AGV or AMR and a positioning block on the ground in the driving area. The AGV or AMR determines its position and direction by calculating the gyroscope deviation signal and collecting the ground positioning block signal. This achieves the automatic guidance of AGVs or AMRs.

The basic working principle of the laser navigation method [96] is to install a laser reflector with a precise position around the AGV/AMR travel path. The laser positioning device installed on the AGV/AMR emits a laser beam, and determines its current position and direction according to the signals reflected from different angles to realize the guidance of the AGV/AMR.

The visual navigation method [97,98] is a new type of navigation method which is rapidly developing and maturing. During the driving of an AGV or AMR, a charge-coupled device camera and sensor dynamically acquire the image information about the environment surrounding the vehicle and compare it with the database to determine the current position and decide on the next driving state. The visual navigation method does not need to manually set any physical path and theoretically has the best navigation flexibility. With the rapid development of computer image acquisition, storage, and processing technology, this navigation method is becoming more and more practical.

Fig. 2 shows the structure of an industrial robot system. The robot obtains external information through the vision system, then calculates the target parameters using software, and finally uses the control hardware to complete specific tasks. The role of vision is to allow the robot to simulate the human visual system, obtain image data information in the visual range through the vision sensor, analyze and judge the image data using the processor in the system, and then realize recognition and tracking. Fig. 3 is the image processing flow of a robot vision system. The advantages and disadvantages of various navigation methods are compared in Table 8.

3.3. Visual navigation tracking

In recent years, with the continuous improvement of chip performance and digital image processing technology, visual navigation technology has developed rapidly. Visual navigation uses AGV on-board cameras to dynamically obtain environmental images, obtain navigation parameters (car position, speed, attitude, etc.) through image detection, and plan the required path to realize the navigation and control of the car. At present, visual navigation technology is widely used in tracking.

Autonomous robots can move, decide actions, and complete tasks without any human intervention. The main subsystems are sensors, motion systems, and navigation and positioning systems. The operation of each component is coordinated to consistently accomplish the desired task [99]. The general process of the mobile robot is explained in Fig. 4. Mobile robots based on vision sensing can complete tasks accurately. The input data is a kind of visual information in an image format, which is processed and analyzed by the controller algorithm to convert it into useful data for the performance of the requested task [100]. Fig. 5 shows

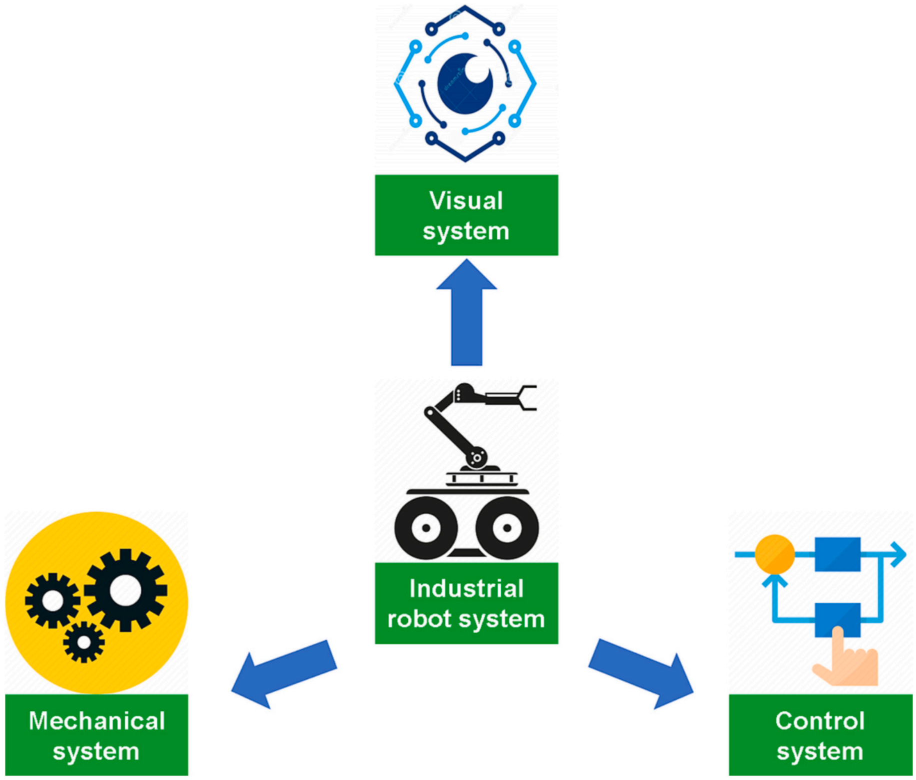


Fig. 2. Industrial robot system composition.

Fig. 3. Visual image processing flow.

Table 8
Types of navigation methods.

Types	Navigation method	Main strength	Main weakness
Fixed Path navigation	Electromagnetic navigation	High control accuracy and reliability, little pollution and di, free from sound and light.	Long construction time, high cost, difficult path reconstruction and expansion.
	Optical navigation	Low wire laying costs, possible to easily change or expand the path.	Floors and reflective tape must be kept clean and level
	Tape navigation	Low path laying costs, possible to easily change or expand the path.	Easily affected by surrounding metal materials, the tape is easily contaminated.
Free route navigation	Inertial navigation	Advanced technology, strong flexibility.	High cost, gyroscopes are sensitive to vibration.
	Laser navigation	High positioning accuracy, applicable to complex environments.	High system cost; high position of the scan head.
	Visual navigation	Hands-free setup of physical paths, flexible and practical.	Poor real-time performance and high system cost.

a basic vision system of a mobile robot.

In the following sections, the most common and effective visual navigation tracking control methods are presented and some recent studies of mobile robot control systems are explained and discussed. The abilities and weaknesses of each model and algorithm are summarized in Table 9.

Monocular vision systems have only one camera mounted on the robot to capture images of the surrounding environment [101–105]. Cameras must be pre-calibrated to obtain feature information from images captured by a single camera. Edge detection and color detection are examples of methods used in monocular vision systems to distinguish objects or obstacles in images. A monocular vision system needs to move to two different points to obtain a single three-dimensional item of information of an object. In this case, the fields of view of the eyes usually do not overlap, or may only overlap each other a little. Monocular vision also cannot give precise values for position and distance. Furthermore, monocular vision is easily disturbed, leading to misinterpretation and computation of vision. Kovacs et al. [103] provided a fully autonomous navigation system using only monocular cameras for navigation and environment mapping of small exploratory robots using jumping motion. A real-time obstacle detection method based on single-camera computer vision was proposed by Tsai et al. Sun

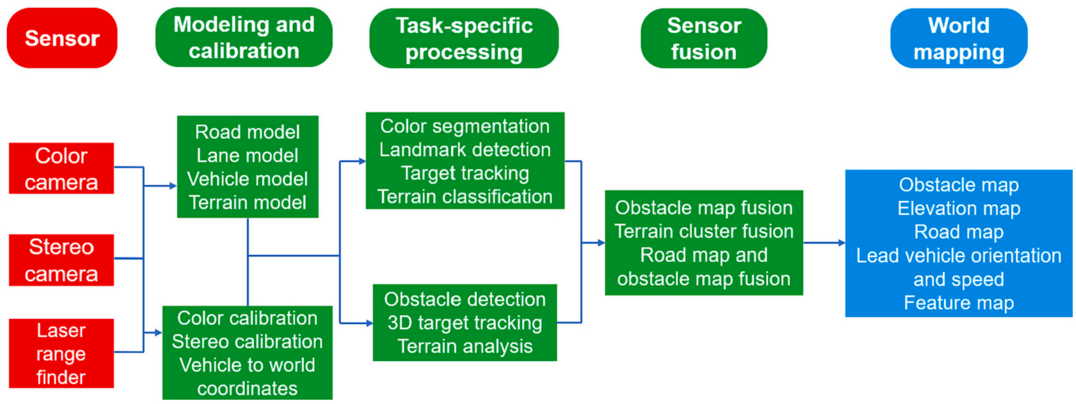


Fig. 4. Block diagram showing the flow of the mobile robot.

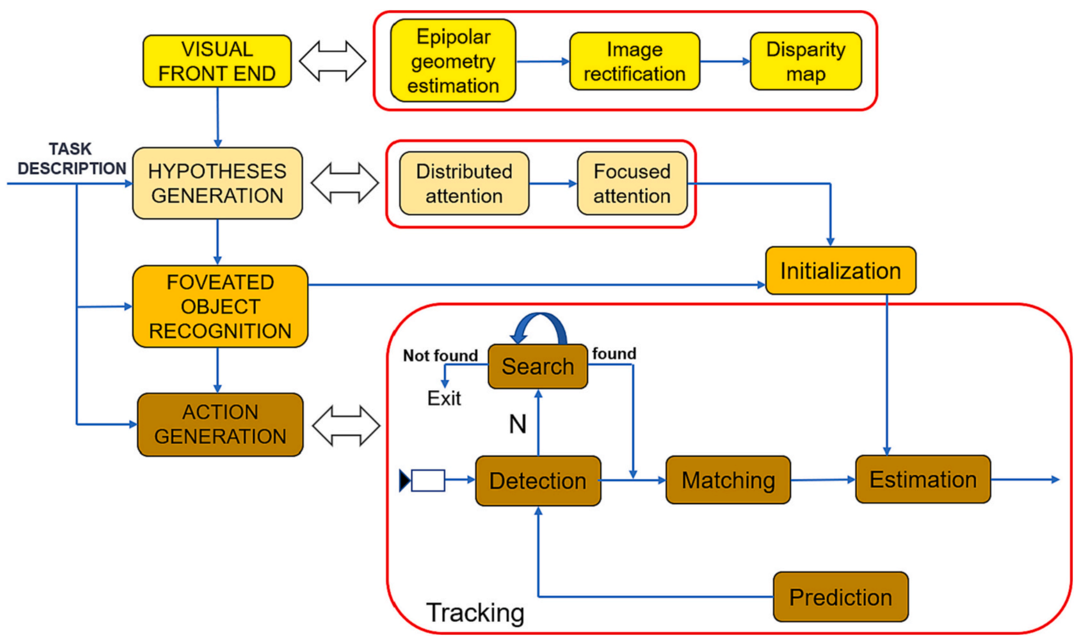


Fig. 5. Basic vision system in the mobile robot.

et al. [105] proposed a navigation system with accurate and real-time motion estimation and map reconstruction capabilities.

There is also a stereo vision-based navigation system [106–108], which consists of two identical cameras mounted on the robot for image acquisition, and this vision system is more able to predict the distance of objects, similar to the stereo vision of humans. Due to the high accuracy requirements of camera alignment, implementing such a stereo vision system is difficult and requires specialized skills or high-precision machines, which can lead to very high costs. Sadruddin et al. [11] proposed a robust fusion framework based on EKF. This design enables the velocities estimated from stereo vision to be directly fused into the EKF, which is less affected by vision-related orientation errors. Stereoscopic keyframe-based autonomous visual-inertial navigation to support the entire navigation system was proposed by Chae et al. [106], which can run on-board without additional graphics processing units.

The main applications of deep learning, which are closely related to the visual navigation technology of mobile robots, have been developed in the past few years [50,109–111]. Ruan et al. [50] proposed an end-to-end mobile robot navigation method based on deep reinforcement learning, and the mobile robot can reach the predetermined target without colliding with obstacles. A hybrid CNN and local image feature architecture for navigation was proposed by Zhao et al. [109]. A robot was designed by Sadeghi et al. [110] to use deep CNN and transfer learning to precisely identify its own location and navigate a specific area. Tai et al. [111] combined CNN and fully connected layers into a complex decision-making form to perform steering control of mobile robots. The results show that the model has high obstacle avoidance performance, like human decision-making.

Visual servoing is an important method of visual navigation. Machkour et al. [112] conducted a comprehensive survey of the state of the art in visual servoing systems, discussing the application of classical methods and new methods based on deep neural networks in robotic visual navigation. Ahmadi et al. [113] designed a vision servobased navigation method allowing robots to accurately follow crop rows. In order to improve the navigation control effect of indoor mobile robots, the visual servo technology was combined by Huang et al. [51] to study the navigation control method of indoor mobile robots. Wang et al. [114] proposed an adaptive algorithm based on global location information in natural feature matching. In addition, an odometer and an attitude heading reference system are included in the servo system to measure the orientation and velocity information of the trajectory. Learning of visual features, predictive dynamics models, and reinforcement learning of visual servo mechanisms were combined by Lee et al. [115].

Table 9
Summary of technologies for visual navigation tracking.

Robot type	Technology	Contribution	Strength	Weakness
Wheeled Mobile Robot (WMR)	Monocular vision	Development of visual navigation method based on monocular vision [101–105]	Simple system structure	Susceptible to interference
WMR	Stereo Vision	Development of a Stereo Vision Based Navigation System [106–108]	Better predicting the distance of objects	High cost
WMR	Deep Learning	Applying deep learning to visual navigation systems [50,109–111]	Makes control decisions quickly	Inaccurate in a continuous state
WMR	Visual servoing	Combines visual features, predictive dynamics models, and visual servos [51,112–115]	Induces computational complexity and time consuming	

4. Integration of recognition and tracking

AGV/AMR recognition and tracking technology involves self-positioning, environmental perception, map construction, path planning, and many other aspects. Although visual navigation has the advantages of convenient route setting, less susceptibility to electromagnetic field interference, lower requirements for the working environment, and higher intelligence, it also has shortcomings, such as being easily affected by environmental changes and the large amount of data it requires. Improvement of the real-time control, robustness, and practicability of AGV/AMR visual recognition and tracking systems has always been the goal of experts and scholars in this field. In recent years, with the development of machine vision software and hardware technology, some integrated recognition and tracking technologies have emerged in the field of AGV/AMR visual recognition and tracking, including path recognition technology based on AI, sensor fusion, and visual SLAM.

4.1. Recognition and tracking based on AI

In an unstructured environment, the key to realizing AGV/AMR visual recognition and tracking is to improve its environmental cognition and autonomous exploration capabilities. AI approaches, such as deep learning, support vector machines, neural networks, fuzzy algorithms, GA, and clustering algorithms, are effective ways to achieve the accurate perception of the environment. In recent years, many researchers have begun to apply AI algorithms to path region recognition in unstructured environments. For example, Lee et al. [116] used algorithms such as scale-invariant feature transformation and acceleration robust features to describe the local environmental features of the navigation area, and studied outdoor self-localization and path information recognition methods for mobile robots. An unstructured path recognition and robot guidance method based on fuzzy rough sets was proposed by Zhao et al. [117], which accurately described the robot's navigation path. Support Vector Machine (SVM), a linear classifier for binary classification of data, was applied by Zhang et al. [118] to the geometric parameter extraction of unstructured roads. Shape, width, and position data are put into the training sample space, and an SVM classifier is used to identify unstructured road regions. Zhu et al. [119] applied KF and recurrent fuzzy neural network to the robot navigation algorithm and used the KF to plan the motion of the robot and the recurrent fuzzy neural network to realize the robust control of the robot's motion, which made progress in the robot's navigation algorithm.

4.2. Recognition and tracking based on sensor fusion

Sensor fusion organically combines visual recognition and tracking with traditional inertial, GPS, laser, and other navigation technologies to achieve complementary advantages and improve the control accuracy and robustness of the system. This technology offers an important way to solve the defects of visual recognition and tracking, such as the large amount of data processing required and the susceptibility to the lighting environment, and it is also an important innovation direction for AGV/AMR recognition and tracking at present. Table 10 shows studies based on sensor fusion algorithms.

State estimation is a common step in data fusion algorithms, since observations of a target may come from different sensors or sources, and the goal is to obtain a global target state from the observations. Table 11 shows studies mainly based on the state estimation method.

4.3. Recognition and tracking based on visual SLAM

Visual SLAM means that when the mobile robot moves in an unknown environment, the mobile robot uses the onboard camera to locate itself according to the perception of the surrounding environment and build a map at the same time. SLAM does not need to set any trajectory in advance, and it is convenient to change the recognition and tracking route, realize real-time obstacle avoidance, and helps improve the autonomy and environmental adaptability of AGVs and AMRs.

Feature-based methods have been the most used methods in SLAM. It is necessary to extract different features from the images to obtain only useful features. The most commonly used algorithm for SLAM is ORB-SLAM, a 3-D positioning and map construction algorithm based on ORB feature, which is a very fast feature extraction method [127,128]. The problem with this algorithm is that many input parameters need to be tuned. The work proposed in [129] attempts to reduce the number of parameters and make the visual SLAM platform and environment independent, but does not achieve the performance of ORB-SLAM.

Direct methods use the pixel information of each frame to track the pose of the robot and map it. They use pixel-to-pixel luminance information and attempt to estimate pose by optimizing the iterative process and reducing the initial photometric error [130]. Some of the more popular direct methods, such as Direct Sparse Odometry(DSO) [131], Large Scale Direct MonocularSLAM(LSD-SLAM) [132], and Dense Tracking and Mapping(DTAM) [133], use monocular vision as their primary sensor. DSO is an optimization of the photometric error model using some key points in the image. LSD-SLAM can build large-scale, consistent maps of the environment. DTAM is a single-pixel based feature detection and tracking method. Some use RGB-D sensors as their primary sensors, such as Kinectfusion [134], continuous [135], and Bundle Adjusted Direct RGB-D SLAM (BAD-SLAM), which allows the use

Table 10
Different sensor fusion algorithms.

Fusion Algorithm	Classification of Fusion method	Sensors/ Data fusion
Kalman filter [79]	State estimate	A visual navigation system and inertial navigation system
Particle filter [120]	State estimate	Optical camera, sonar, and odometry
Bayesian Network [121]	Decision	LiDAR
Dempster-Shafer [122]	Decision	Vision and encoder

Table 11
State estimation sensor fusion algorithms.

Sensors	Fusion Method	Contributions
Visual, inertial, and magnetic [123]	EKF	Solves the Self-Motion Estimation Problem of Handheld IMU Camera Systems.
Encoder, inertial sensor, active beacon [124]	Unscented Kalman Filter (UKF)	Minimizes sensor position and orientation errors.
Visual and inertial [125]	EKF & UKF	Integration of visual and inertial sensor data to estimate motion and structure simultaneously.
Visual system and robot odometry [126]	KF	Combination of vision system and odometry measurements to calculate actual position of robot.

of rich information in global optimization, with precise trajectories [136].

Structured light-based RGB-D camera sensors [137] have recently become cheap and small. Such cameras provide 3-D information in real time but are most likely to be used for indoor navigation because the range is less than four or five meters and the technique is very sensitive to sunlight. For the RGB-D V-SLAM approach, see [138,139].

Event cameras are biologically-inspired imaging sensors which provide "unlimited" frame rates by detecting visual "events" (i.e. changes in images). Such a sensor has recently been used in V-SLAM [140,141]. Although V-SLAM provides very good results, all these V-SLAM solutions are error-prone because they are sensitive to lighting changes or low-texture environments. Furthermore, image analysis still requires a high level of computational complexity. The strengths and weaknesses of vision-based SLAM are shown in Table 12.

5. AGV/AMR based recognition and tracking in civil engineering

AGVs and AMRs bring new opportunities to the development of civil engineering disciplines. These technologies integrate the entire life cycle of civil engineering construction, monitoring, and maintenance, and profoundly change the development of civil engineering science, technology, and engineering. Furthermore, they are widely used in many civil engineering projects such as roads, bridges, tunnels, airports, and power substations.

5.1. Automated road inspection and maintenance

Roads are indispensable civil infrastructure for human society and daily life. However, road pavements are affected by unfavorable factors over decades of use, which inevitably cause distress and accidents. AGVs/AMRs, artificial neural networks [142,143], and deep learning [144] have been introduced into road condition monitoring and diagnosis, which is of great significance to the improvement of road operational efficiency and safety for the remaining service life.

Table 12
Summary of strength and weakness of visual SLAM.

Visual-based SLAM	Feature-based	Direct	RGB-D	Event-based
Strengths	Low size, weight, power, and cost	Semi-dense maps without feature detection	Very dense maps with direct depth detection	High varying frame rate
Weaknesses	Sensitive to texture and light	High computational cost, requires photometric calibration, usually GPU-based	Sensitive to daylight, can only work indoors, very high data volume, very short distances	Sensors are expensive and can only detect changes in the environment

5.1.1. Road pavement distress detection

Nguyen et al. [145] designed and developed a 4-degrees-of-freedom (DoF) arm, which was then integrated with a robot for efficient image capture using vision and thermal imaging cameras. The robot system uses the latest method involving CNN to perform crack detection on the collected data, which is verified on various test images. As a result, the robot can output multiple state diagrams of the inspected infrastructure, including crack diagrams, temperature diagrams, and deterioration diagrams, to provide an overall picture of the health of the structure.

The overall architecture of the robot system is shown in Fig. 6. It has a module which controls the movement of nondestructive evaluation (NDE) sensors (ground-penetrating radar(GPR), electro-rheological sensors, and thermal cameras), high-resolution cameras, and linear actuators through a microcontroller and a relay board. It also has a module for the positioning and navigation of EKF sensor fusion. In addition, the system has a wireless connection between the robot and the human operator for an optional manual control and monitoring system. The robot arm and robot are shown in Fig. 7 [145].

This robot system integrates NDE sensors composed of GPR, electrical resistivity, and thermal cameras, as well as high-resolution vision cameras. Inspection based on nondestructive testing is related to visual inspection methods [146]. Visual inspection uses two types of images, a high resolution image from a Canon digital single-lens reflex camera and a thermal image from a thermal camera. The two cameras are mounted on a 4-DoF arm to allow the robot to capture high-resolution visual and thermal images of the surface of the inspection area during the movement of the arm. Under a certain moving distance (for example, 3 m), a single visual image is stitched together and then analyzed by the robot using the most advanced CNN to detect cracks. A thermal image is processed and drawn to display a diagram of the thermal state of the surface. The GPR is used to generate a map of the true attenuation conditions on the ground, which is used to verify the results of the visual inspection.

The robot system is also equipped with GPS and IMU, which are fused with odometer data using EKF [147] to allow the robot to accurately locate and navigate in the inspection area. To simplify positioning and motion planning design, it is assumed that the speed direction of the robot is aligned with the heading direction. Therefore, a unicycle kinematics model is used to approximate the robot's motion. Using the state dynamics model and the output relationship, the EKF is designed to estimate the position and attitude of the robot.

At the end of the robotic arm is a camera assembly equipped with a high-resolution Canon T3i, a thermal camera, and a low-resolution webcam. The rotation of this 2- degrees-of-freedom component is controlled by two servo motors, which are controlled by an Arduino microcontroller using a ROS driver, as shown in Fig. 8.

Although flying is one of the safest modes of transportation [148,149] and aircraft accidents rarely occur, when they do occur they are much more serious than other traffic accidents and may cause greater social impact. Since the structural performance of the surface of airport roads (runways, taxiways, and aprons) is closely related to the safety of aircraft operations, road surface inspection is a basic task for monitoring the airworthiness and reliability of airport road surfaces [150–152]. With the rapid development of the civil aviation industry and other infrastructure construction, there is an urgent need for autonomous intelligent road detection methods [153]. In the past few decades, research on autonomous non-destructive testing and inspection methods for different infrastructures has attracted widespread attention and produced many prototypes [154].

For example, Gui et al. [155] has proposed a new type of airport pavement inspection robotic system (APIRS). The sensor configuration of the robot is shown in Fig. 9. This robot system uses EKF to estimate the position and posture information of the robot based on the position and

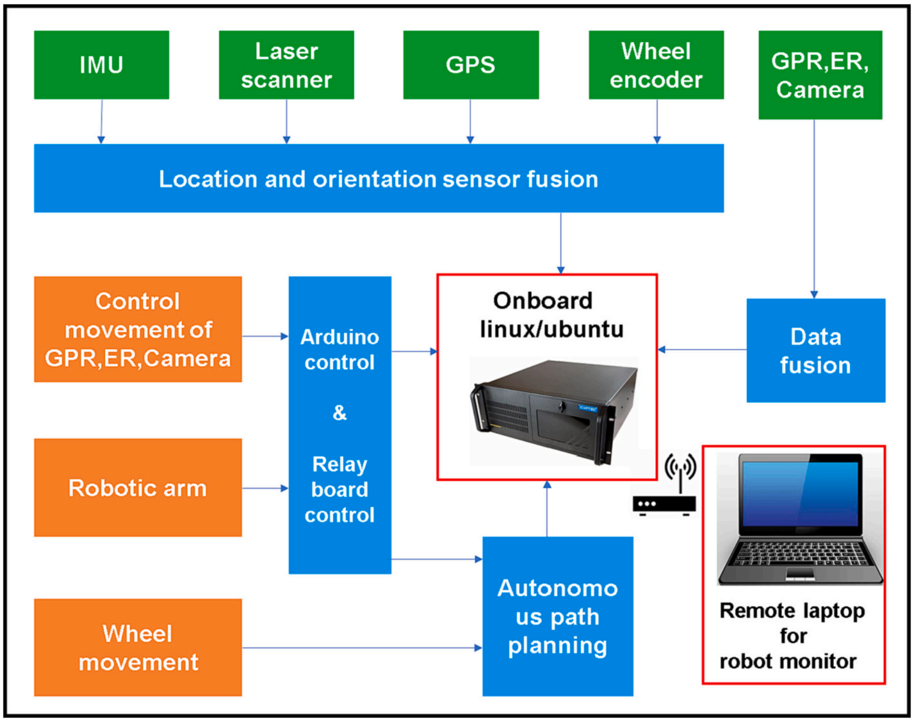


Fig. 6. Architecture of robot system for pavement distress detection.

Fig. 7. Robot arm for pavement distress detection [145].

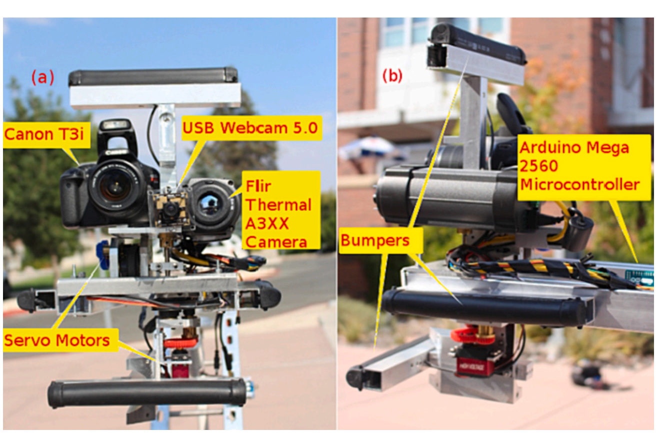


Fig. 8. Camera components of the robotic arm [145].

posture information of the robot observed over a period, as well as the past and present state of the robot. EKF is based on a positioning algorithm and provides optimal position and attitude information based on GPS, IMU, and wheel mileage data. The control system is a PID controller, which takes the positioning data provided by EKF as feedback, and the target positioning data provided by the path planning algorithm as the target value. The control commands include lateral velocity, longitudinal velocity, and angular velocity [155].

To evaluate the performance of the proposed system, Gui et al. used APIRS to perform inspection tasks at a representative airport in northern China, as shown in Fig. 10(a). The inspection area was a rectangular area (1000 m long and 18 m wide) along the centerline of the airport runway. The inspection area is shown in Fig. 10(b).

An AI-based airport runway detection robot solution has been proposed by Chen et al. [156], which solves the problem of high-precision positioning and control of airport runway robots. For airport runway detection robots to control their respective positions and attitudes, this project achieves PI speed control in the inner loop to accurately track the outer loop. The main problem solved by the outer loop is the accuracy,

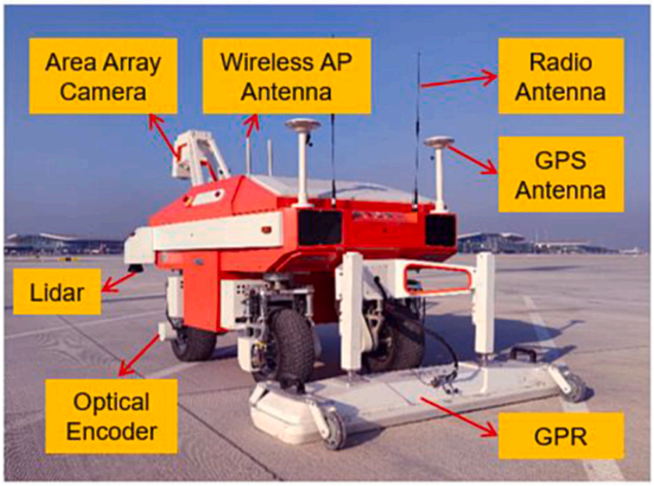


Fig. 9. Sensor configuration of inspection robot [155].

real-time, and speed of the pose control. Therefore, the incremental PID control algorithm is considered in the control of the airport runway robot [156].

5.1.2. Intelligent compaction of roads

Intelligent compaction (IC) is an effective quality control method to improve the compaction performance of roads. Generally, IC technology refers to a roller equipped with a measurement system, including a high-precision GPS, accelerometer, infrared thermometer, and on-board computer reporting system, as shown in Fig. 11. Continuous color-coded map records are maintained, showing the number of rolling passes, compaction strengths, temperature measurements, and the precise position of the roller [157,158]. The use of IC has been demonstrated in engineering practice in projects carried out around the world in the past two decades [159].

In IC technology, GPS is the core equipment. It continuously tracks the position of the roller to maintain a consistent rolling pattern and ensure high-quality road performance. GPS also helps to generate a rolling map as a base layer to help record the precise location of weak points detected by accelerometers and infrared thermometers. A visual odometer (VO) is the means to determine the position and orientation of the robot by analyzing the relevant camera images. VO uses infrared thermal imaging technology, which has the advantage that it can be used under adverse conditions such as fog, smoke, and insufficient light. Due to the relatively high temperature of newly-paved asphalt pavement (usually higher than 115 °C), the collected thermal images can reliably extract the boundary geometry and feature points of the pavement.

Since the compaction standard requires a low-level compaction speed to ensure compaction quality [161], it is reasonable to assume that roller motion can be decomposed into two motion components, namely, the direction of excavation and linear translation. Fig. 12 presents an overview of the proposed method, which includes four main modules: heading estimation, linear translation estimation, lateral position optimization, and global position estimation. First, by using the heading estimation of the geometric structure of the road boundary and the translation estimation of the optical flow technology, the motion of the roller between two consecutive frames is estimated. Next, lateral position optimization is applied to improve the accuracy of the lateral position of the rolls. Finally, the current global position of the roller is estimated by recursively linking the frame-by-frame motion of the roller.

5.1.3. Road pavement sweeping

Pavement cleanliness is essential for maintaining urban hygiene and keeping roads clean and tidy. Mobile robots play a vital role in cleaning, maintenance, and monitoring applications. An increasingly important robot is the cleaning robot, which is programmed to work autonomously or semi-autonomously in indoor [162–164] and outdoor environments [165–167]. Such robots can perform repeated and routine cleaning in a predetermined geographical environment. However, using a cleaning robot with a fixed configuration [168,169] means that it cannot drive on roads of different widths, and cannot clean when a fixed obstacle blocks the road, and there is not enough space for the robot to pass. Examples of robots with fixed dimensions are shown in Table 13.

The road cleaning self-reconfigurable robot Panthera shown in Fig. 13 was first described in [175], and has design and reconstruction capabilities. Panthera is able to use kinematics and control inputs to operate safely and clean road surfaces. Using RGB data sensors and new semantic segmentation methods, such as SegNet [176] and DeepLab [177], and the pixel coordinates of the road surface, the real coordinates and estimated values of the road width in different parts of the image can be determined. According to different estimated road widths, the control schemes of the robot can be developed. The ROS [178] makes decisions based on RGB-D sensor input to control the speed of the screw motor, the speed of the wheel motor, and the heading angle of the steering device. The ROS-based block diagram is shown in Fig. 14. The robot can adaptively change its width in a dynamic environment. Panthera drives in the center of the road, parallel to the road, as shown in Fig. 15. When performing cleaning operations, it can adaptively change its width during movement(Fig. 16).

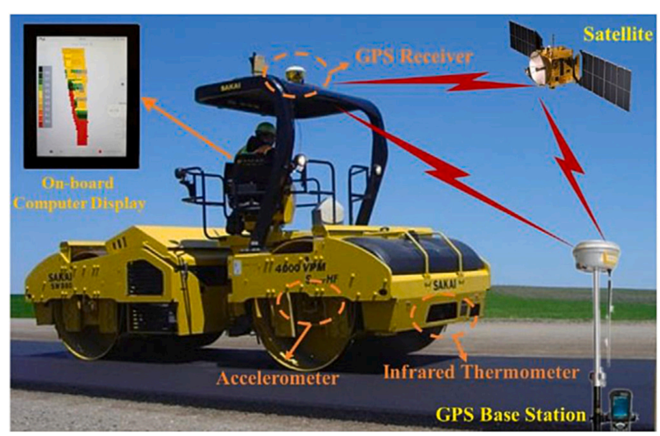


Fig. 11. Example of a typical IC technology [160].

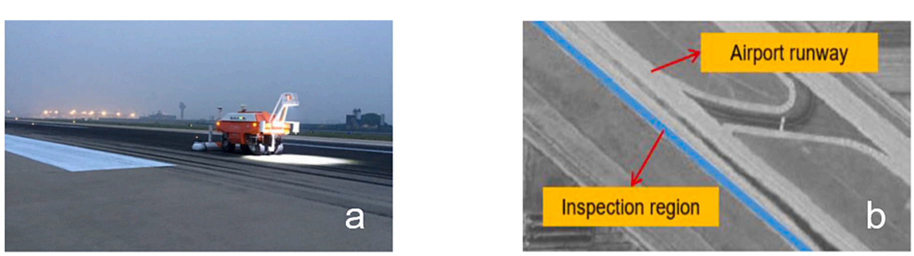


Fig. 10. Real inspection scene(a) and Inspection working region (b) [155].

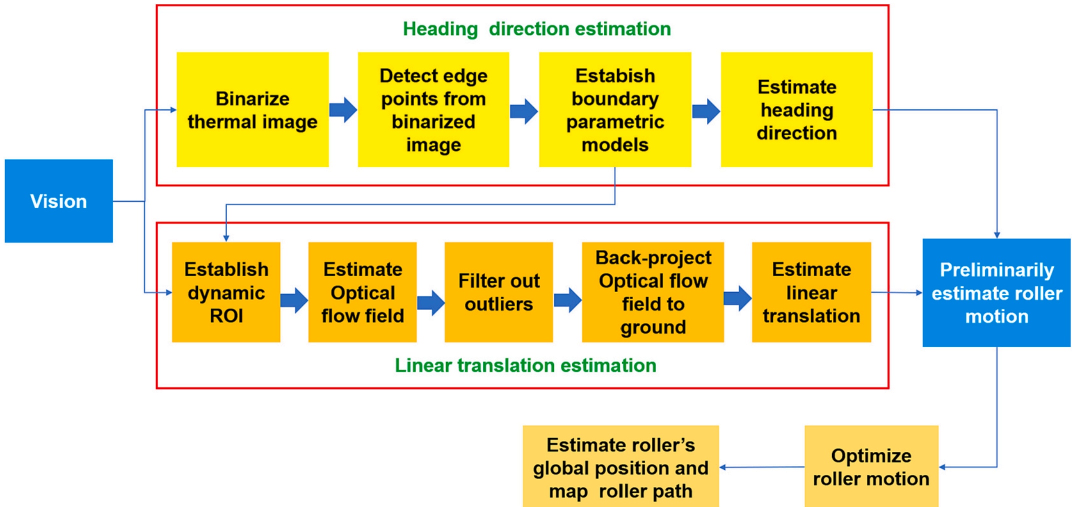


Fig. 12. Flowchart of method for roller path tracking and mapping.

Table 13
Existing pavement cleaning vehicles.

Specifications	SS	MN	GM636	CN101
Power source	24 V	48 V	Diesel	Diesel
Noise	80 dB	–	78 dB	80 dB
Holonomic	No	No	No	No
Sweeping speed	6 km/h	7 km/h	8 km/h	8 km/h
Brush dia. (mm)	700	800	750	700
Weight	50 Kgs	400 Kgs	600 Kgs	600 Kgs
Ref.	[170]	[171]	[172]	[173]

Fig. 13. Panthera: reconfigurable pavement sweeping robot [174].

A segmented road surface on a mask-based deep convolutional neural network is used as the input of the closed loop feedback control method, which enables the robot to accurately adjust the width requirements during movement. The PID controller realizes the smooth control and driving performance of the robot. GA [147] and PID parameters are used to control the speed of the motor, fuzzy logic controls the PID controller [179], and the temporary dynamic behavior of the direct-current (DC) motor is self-tuning PID [180]. A reliable controller is used to control the position and speed of the steering unit and the lead screw DC motor. Because the reconfigurable robot has a flexible and dynamic gait, it is necessary to use the parameter input of the sensor (for example, the feature of the object in vision) for feedback control to realize the smooth motion of the robot.

5.2. Automated bridge inspection

The monitoring, maintenance, and repair of bridges are vital at the national level. Recent studies have emphasized the necessity of bridge maintenance and evaluation [181,182]. Bridge health monitoring (BHM), is the application of inspection technology to bridge structures, and involves the collection of quantitative data from various sensors located inside or on the surface of a structure [183]. BHM can be divided into three key aspects: construction control, routine monitoring, and distress detection [184]. It is widely dependent on mobile robot platforms, which are widely used for the intelligent inspection of bridge decks, bridge cables, and underwater bridge piers.

5.2.1. Bridge deck inspection

Bridge deck condition assessment is an important part of bridge health maintenance. Accurate condition assessment and monitoring of the deterioration of concrete bridge decks require the use of a variety of NDE techniques and automated data collection and analysis. Using autonomous mobile robots as platforms carrying various NDE sensing systems, data can be collected quickly and simultaneously. In addition to NDE sensors, the robots are equipped with various navigation sensors. The robot-assisted bridge inspection tool (RABIT) for bridge decks is capable of fully autonomous data collection. To this end, RABIT has implemented four non-destructive testing techniques: the resistivity, GPR, impulse echo, and ultrasonic surface wave methods. The RABIT survey also supplements visual inspections by collecting high-resolution images of the bridge deck surface, which can be used to map cracks and record bridge deck spalling, previous repairs, etc.

Several mainstream robot platforms are shown in Table 14. La et al. have developed an EKF-based design to combine a wheel encoder, onboard IMU, and high-performance GPS for robot localization and navigation [188]. As Fig. 17 shows, the motion of the robot covering the detection area is composed of a linear trajectory and an omnidirectional trajectory. The robot can accurately collect images and NDE data along a straight line. At the end of each straight line, omnimotion is used to realize the safe turning of the robot. Based on this trajectory planning, a robot motion control method based on potential function has been designed [147]. Moore et al. [189] used a ROS software package called drobot_localization, which uses GPS and IMU data to navigate through EKF. Fig. 18 shows the robot's trajectory during an example outdoor navigation process.

Recently, increasing attention has been paid to the development and

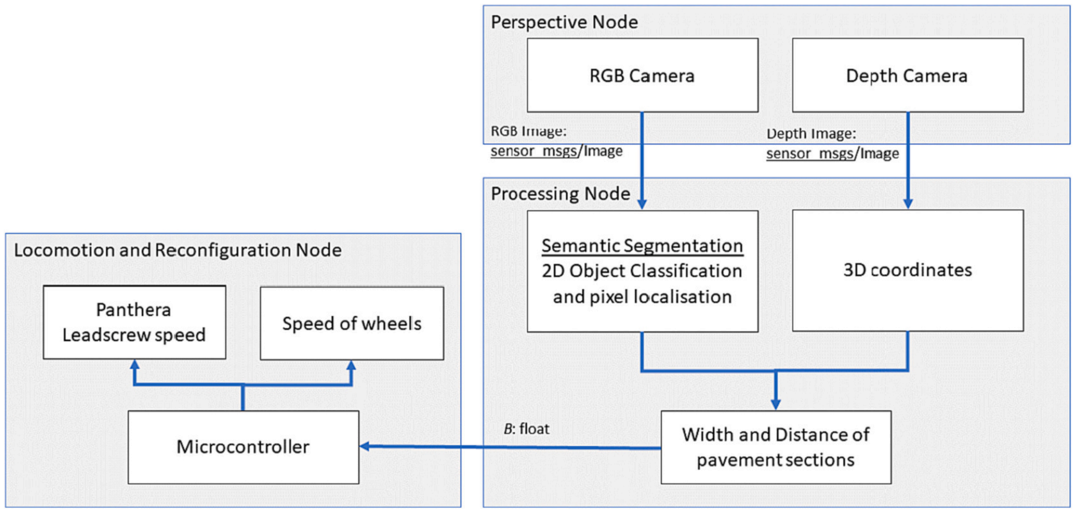


Fig. 14. Block diagram of reconfigurable mechanism based on vision [174].

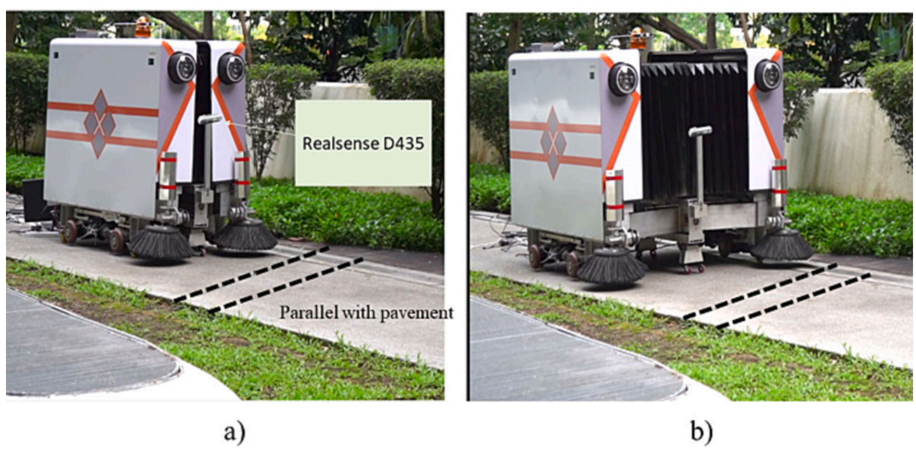


Fig. 15. Panthera platform. (a) minimum width, (b) maximum width [174].

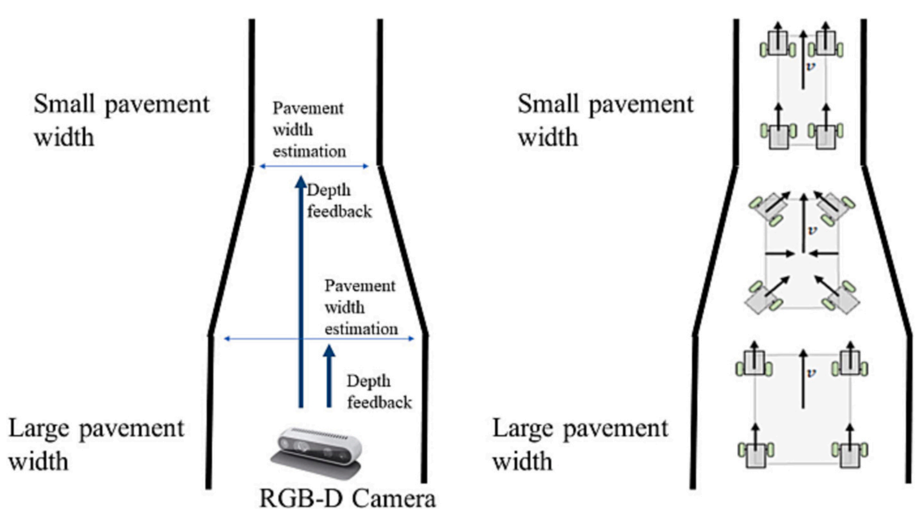
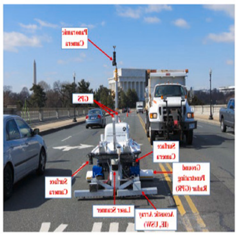
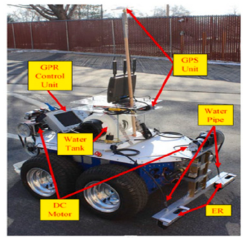
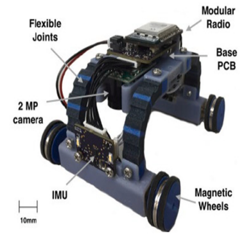
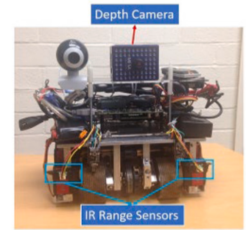


Fig. 16. Panthera adapting to dynamic varying pavement width [174].

use of semi-autonomous and fully autonomous robots for civil infrastructure (especially bridges) using NDE and BHM. A variety of robots have been developed, the main ones being advanced robotics and automation (ARA) laboratory robots, crack detection and mapping (ROCIM) robots, and RABIT [190–193].

A comparison of the different robot platforms shown in Table 15 reveals that different robot platforms are equipped with different software and hardware, and sensor fusion technology causes them to

Table 14
Robotic platforms for bridge deck inspection.

Set-up of robotic platforms			
			
RABIT [179]	Seekur Jr. Robot [185]	BridgeBot [186]	Magnetic Wheeled Robot [187]

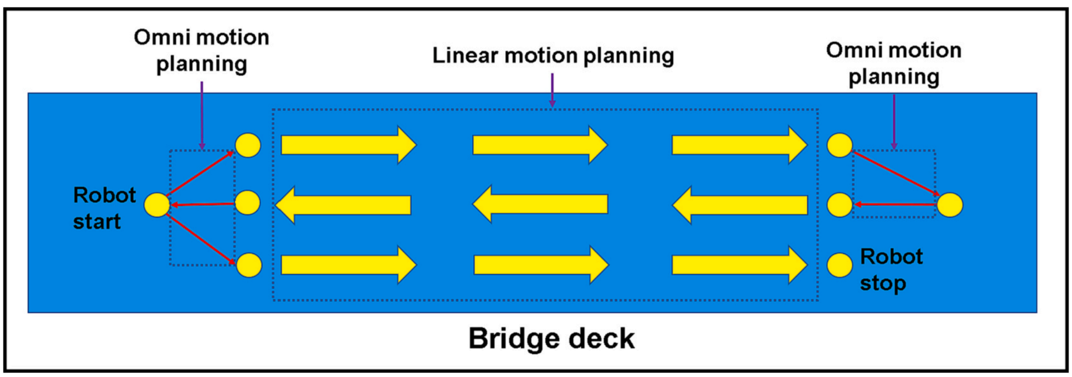


Fig. 17. Schematic diagram of the robot's motion planning on the bridge.

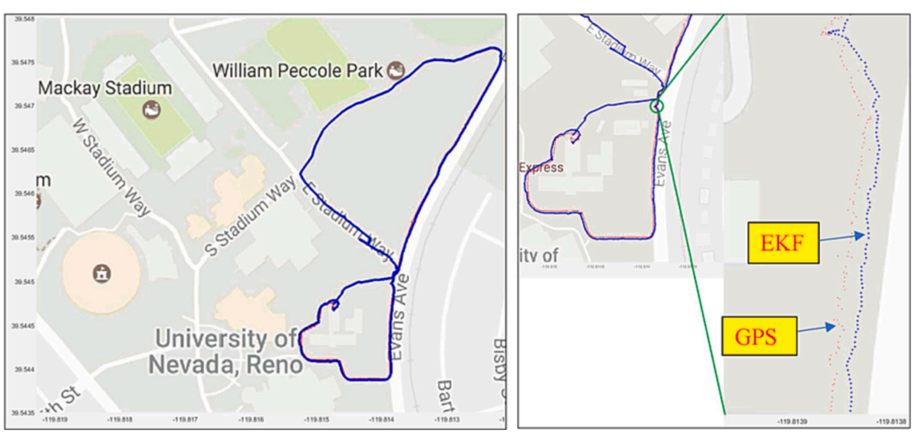


Fig. 18. Trajectory of our outdoor navigation using the therobot_localizationROS package (left). Red dots indicate GPS, and the dots show the output of the EKF. A close-up view of the EKF and GPS signals (right) [189]. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 15
Comparison of robotic platforms equipped with different sensors.

Robotic Platforms	Type	Sensors			
		Vision	Radar	Electric	Acoustics
RABIT [193,194]	Wheeled	Canon camera	GPR array	ER probe	IE and USW array
ROCIM [195]	Wheeled	Canon camera			
ARA Lab [145,185]	Wheeled	PrimeSense Camera Stereo camera	GPR array	ER probe	

operate in an intelligent and autonomous way in terms of path planning and trajectory generation. Gucunski et al. [193] have designed a robot navigation system suitable for rectangular measurement areas of linear bridges. It consists of linear scans, each scan covering a 1.8 m wide strip. By full motion planning, the robot is navigated to the next line at the end of each line. The navigation program has two sub-routines: linear motion planning (LMP) and omni motion planning (OMP). The robot first moves to the desired position in a straight line under the control of the LMP program. At the turning point, controlled by the OMP program, the robot continues in a zigzag trajectory. During the data collection process, the robot stops at predetermined distances.

5.2.2. Bridge cable inspection

As the load-bearing component of cable-stayed bridges, cables need to be tested and maintained regularly. Robots can carry detection sensors for cable testing in various ways, including non-destructive testing and visual testing. Nondestructive testing is the use of climbing robots to carry nondestructive testing equipment to detect broken wires inside cables, including ultrasonic testing [196], radiographic testing [197], and other methods. Visual inspection allows users to use the camera carried by the climbing robot to collect images, and then apply image stitching, statistical inference, convolutional networks, and other methods of analysis to identify surface defects [198].

Zheng et al. [199] developed a palm-based cable climbing robot. The low-level controller is designed to use joint position and torque control to realize the onboard system. An autonomous climbing algorithm has been developed. The robot uses detection data to ensure that the gripper module is close to the surface of the cable or close to the shape of an obstacle, and then performs trajectory planning. The obstacle crossing process and method of the climbing robot have been analyzed by Ding et al. [200]. A dynamic obstacle crossing model of the driving wheel and the driven wheel of the climbing mechanism was established, and kinematic and dynamic analyses were carried out. According to the movement curve, speed and driving torque are required by the robot in the process of crossing obstacles. According to the motion curve, the robot realizes the process of crossing obstacles through the control of speed and driving torque, which improves the stability of the robot at high altitude.

The robot platform used by Xu et al. is shown in Fig. 19. Xu et al. [201] have proposed a climbing robot for bridge cable inspection. The main control system collects the angular velocity information of the driving wheel through the encoder, detects the running state of the motor, and recognizes the current position of the robot. A laser rangefinder is used to measure the distance between the robot and the tower to prevent collisions, and the GPS module detects the working position of the robot. To verify the adaptability of the robot to the reality of bridge inspection, field tests were carried out on cable-stayed bridges. As the robot crawls along the cable, the detection system is automatically activated to record the distress to the surface. The installation and testing settings are shown in Fig. 20.

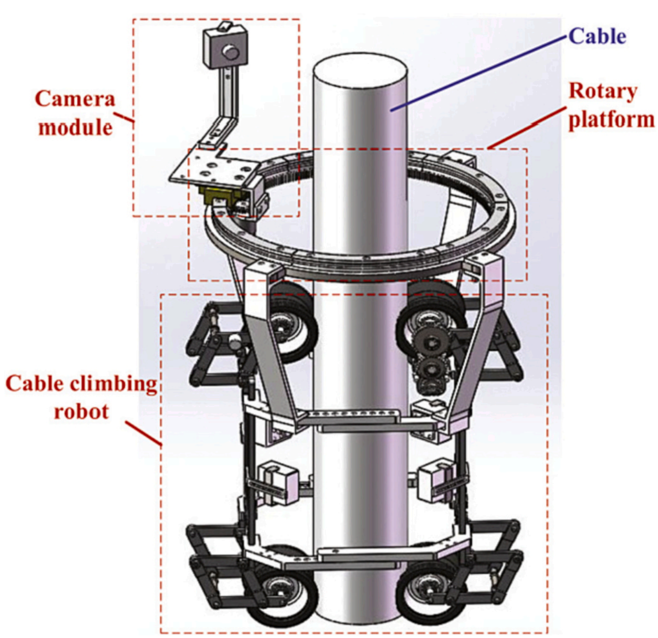


Fig. 19. Schematic representation of cable inspection platform [201].

5.2.3. Inspection of underwater bridge piers

Underwater robots are mainly responsible for inspecting the underwater parts of bridge infrastructures. One of the earliest studies of this type emphasized the importance of human inspectors inspecting accessible or inaccessible areas of bridge infrastructure [202]. The platform uses cameras to show the underwater pier sections of a bridge [202]. However, the overall effectiveness of visual inspection is severely affected by the clarity of the water and the weather conditions, which are some of the limitations of underwater independent visual systems. Over the years, this field has expanded, and has received attention in post-disaster inspections and regular structural health monitoring (SHM) of bridge piers [203]. Many unmanned maritime vehicles, unmanned underwater vehicles, unmanned submersible vehicles (USVs), and remotely-operated vehicles (ROVs) have been deployed in the past, including semi-automatic sensing platforms, muddy water, sea-RAI, and VideoRay and YSI® ecological map instruments [202–204]. Table 16 indicates that the number of underwater robot platforms is limited, and most rely on visual sensory information to conduct the SHM of underwater bridge structures. Due to the various challenges of underwater detection, further research is needed to improve the perception of data acquisition and tools and techniques of analysis which can be used for the underwater SHM of bridges in future.

The Sea-RAI unmanned surface vehicle shown in Fig. 21 is a custom platform built by AEOS based on two 6-ft catamaran hulls. It is capable of autonomous waypoint navigation and supports remote operation via wireless F4W 802. 11. Sea RAI carries a Disen acoustic camera for underwater inspection and three cameras (front, back, and hemispherical) for observation above the waterline.

He et al. [205] have proposed a trajectory tracking control scheme. The goal of this controller is to provide robust tracking performance for underwater robots in attitude-sensitive trajectory-tracking tasks such as underwater docking and dock detection. The controller is composed of a tracking cost controller which ensures the exponential convergence of the position tracking error and a robust switch controller which uses the Lyapunov control function to enable it to deal with modeling uncertainties and external disturbances [205]. A system consisting of ROVs for underwater measurement and inspection and USVs for transporting ROVs to underwater infrastructure has been proposed by Ueda et al. [206]. The system is equipped with GPS and a laser range finder(LRF) is used for self-positioning estimation. USV has GPS, LRF, and IMU for horizontal positioning and camera control. ROV observes the state of bridge piers through the camera and controls its attitude using the depth sensor and IMU sensor [206]. Yamamoto et al. [207] have developed an underwater robot which detects bridge piers. The proportional control is driven by pulse width modulation. One difficulty which is solved is the initial positioning of the robot and the use of thrusters to counter the water flow, or the use of accelerometers to compensate for these water flows to help the robot maintain a fixed position.

5.3. Building construction

In the construction industry, the role of on-site automation has been very limited to date. Increasing automation on construction sites may have major advantages, such as reducing injury rates, handling repetitive tasks, and helping to carry out construction in environments which are currently not feasible. Increasing the degree of automation of construction activities may solve these shortcomings [208]. Therefore, the development of onsite semi-automated and unmanned vehicles is increasing for various construction applications such as wall painting [209], construction component production [210], component assembly [211], seam filling [212], inspection [213], and construction monitoring [214,215]. However, the implementation of unmanned vehicles on construction sites, especially on ground vehicles, is still rare or under-utilized [216]. Asadi et al. [217] presents a mobile robotic system capable of autonomous navigation integrated with scene understanding and object manipulation (Fig. 22).

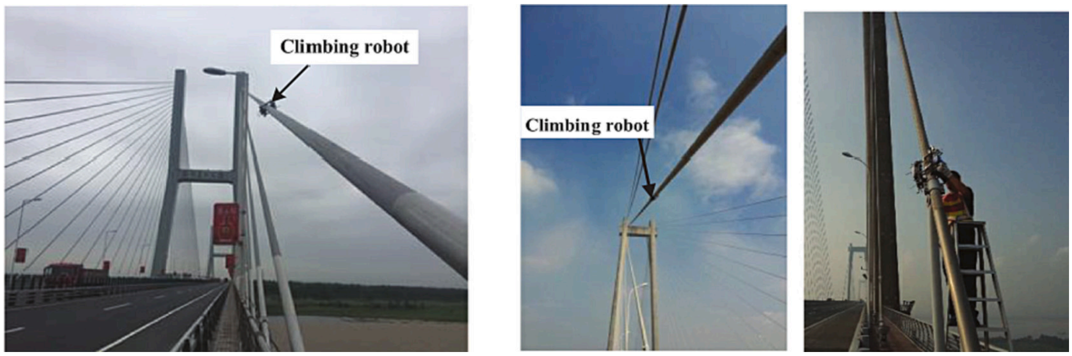


Fig. 20. Using climbing robot in bridge cables [201].

Table 16
Comparison between the underwater robotic platforms.

Robotic Platforms	Type	Sensors
Underwater ROV [202]	USV	Camera
Videoray ROV [204]	USV	Camera Sonar
YSI®Ecomapper [204]	USV	Side-scan Sonar
Sea-RAI [204]	USV	Camera
Muddy Waters [203]	USV	Stereo RGB-D camera ARIS@Snoar

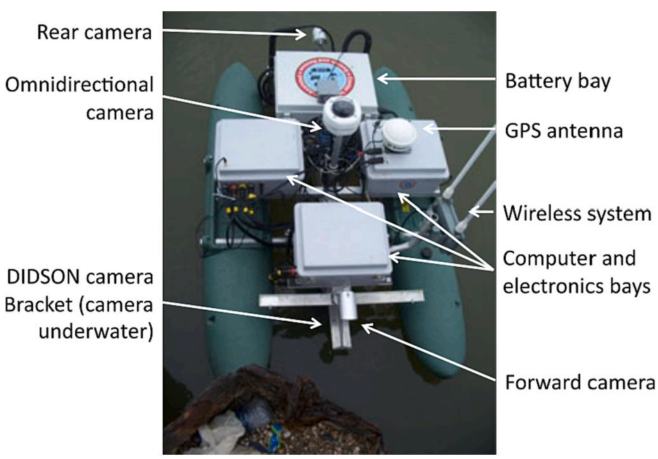


Fig. 21. Sea-RAI with key components labeled [204].

A SLAM-based Ground Robotic Mapping Infrastructure (GRoMI) navigation and object recognition method has been proposed by Kim et al. [218]. A path-finding algorithm for autonomous navigation in an unknown obstacle environment based on the artificial potential field method has been developed. In general, the 3-D color map generated by GRoMI (Fig. 23) has sufficient cloud quality for construction sites and can be used for many construction applications, such as construction progress monitoring, safety hazard identification, and defect detection [218]. Gawel et al. [219] have proposed a fully-integrated sensing and control system which enables mobile manipulator robots to perform construction tasks with millimeter-level accuracy on construction sites. Using a mobile horizon estimator, a fusion of LiDAR positioning update, IMU measurement, and wheel odometer, the estimated state is used as feedback from the robot motion controller to track the reference trajectory of the base and end effector. A model predictive controller is used to plan and track the trajectory of the entire body to complete the task [219]. Semantic navigation and a semantic path planning method for mobile robots on construction sites have been proposed by Karimi et al. [220], who combine the optimal semantic path with adaptive Monte Carlo positioning and navigation, and use the A* algorithm to calculate the shortest path within the optimal path.

5.4. Tunnel inspection

The structural performance of tunnels changes over time because of the degradation caused by natural and manmade impacts, changes in load standards, or the simple effects of aging. Therefore, inspections, evaluations, and maintenance are required to ensure that these structures remain in a safe state and continue to provide reliable service levels. Automated, cost-effective, and thorough inspection of tunnels improve short and long-term safety and increase productivity [221]. Menendez et al. [222] have proposed the integrated ROBO-SPECT system.

The ROBO-SPECT robot system is composed of robotized mobile vehicles which can extend automatic cranes to sizes commonly found in subways and highway tunnels. To measure the width and depth of cracks detected in tunnels, the robot system is equipped with a specially-designed ultrasonic sensor robot tool and a robot arm for high-precision positioning. A set of computer vision cameras is used to detect cracks and other defects on the tunnel lining, and a 3-D laser profiler provides data from evaluation tools to detect tunnel deformation. A set of cameras is attached to the crane, and an internet protocol camera is placed at the end of the arm to achieve additional remote operation modes. Fig. 24 depicts the design of the robot system and its different components. The mechanical design of the system is based on the mechanical design used in the TUNCONSTRUCT European FP6 project [223], which uses similar vehicle, crane, and robotic arm configurations.

Fig. 25 describes the testing of crack detection in a tunnel, including image acquisition, crack detection, stereo image acquisition, 3-D laser profiler scanning (if a crack is detected in the segment), and other defect detection algorithms at the end of the inspection.

Yang et al. [224] built a tunnel inspection robot control system based on NVIDIA Jetson TX2 and STM32F407 in response to the key technical problems of the tunnel inspection robot. A RFID-based positioning scheme has been designed, so that the robot can quickly and accurately obtain location information [224]. A hybrid control algorithm for moving a mobile robot in a general tunnel environment containing multiple static obstacles has been proposed by Verma et al. [225], who report that two sliding mode control strategies are bundled together and implemented to provide a tunnel navigation scheme [225]. An automatic tunnel shotcrete robot based on an eight- degrees-of-freedom shotcrete machine has been developed by Lin et al. [226]. A multi-joint coupling control algorithm based on single-joint dynamic PID control has been designed to obtain the target trajectory data of the robot given by trajectory planning [226].

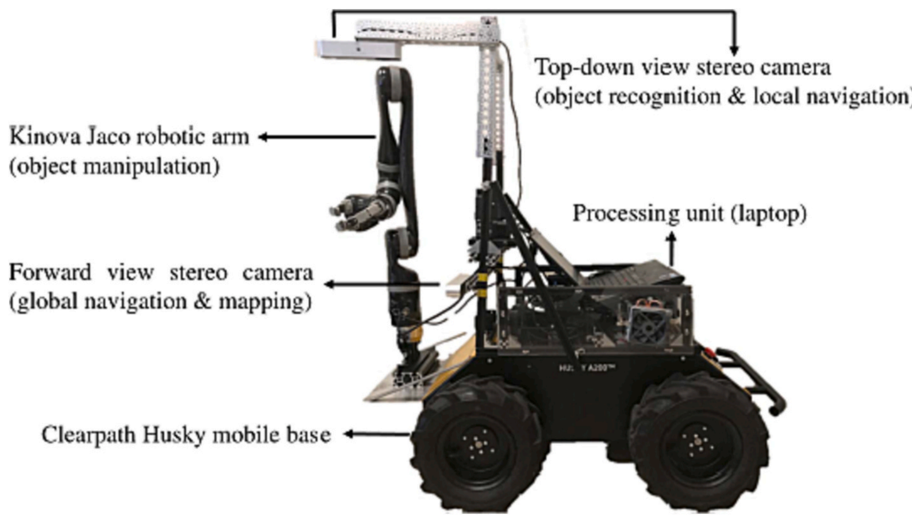


Fig. 22. Automated object manipulation system for construction applications [217].

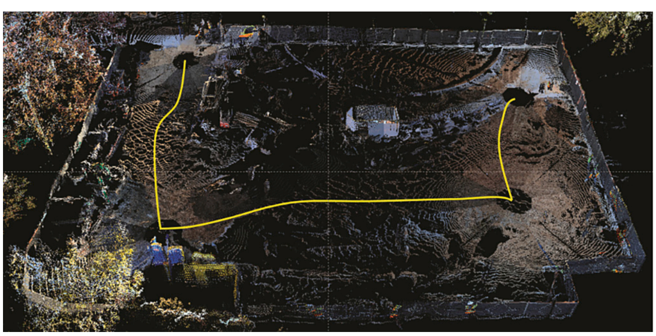


Fig. 23. 3-D point cloud of outdoor construction site generated by GRoMI. The bold yellow line is the trajectory path created by GRoMI [218]. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

5.5. Power substation inspection

As an important part of modern power systems and future smart grids, the safe and stable operation of substation equipment plays a very important role in power systems. To improve the reliability, safety, and intelligence of substations, accelerate the realization of unattended substations, and the automation of substation equipment, detection has become an important topic in the power industry [227]. With the development of robotics, a feasible solution is to develop autonomous mobile robots and then develop accurate automatic inspection methods [228]. Substation inspection robots occupy an important position in research on special robots in the field of power facilities. The robot rat [229] designed by Japan's Shikoku Electric Power Company, Toshiba Corporation, and other research institutions, is a substation inspection robot suitable for 500KV substations. The State Grid Corporation of China has successfully developed a substation inspection robot (see Fig. 26), which is comprises a mobile vehicle platform, infrared and

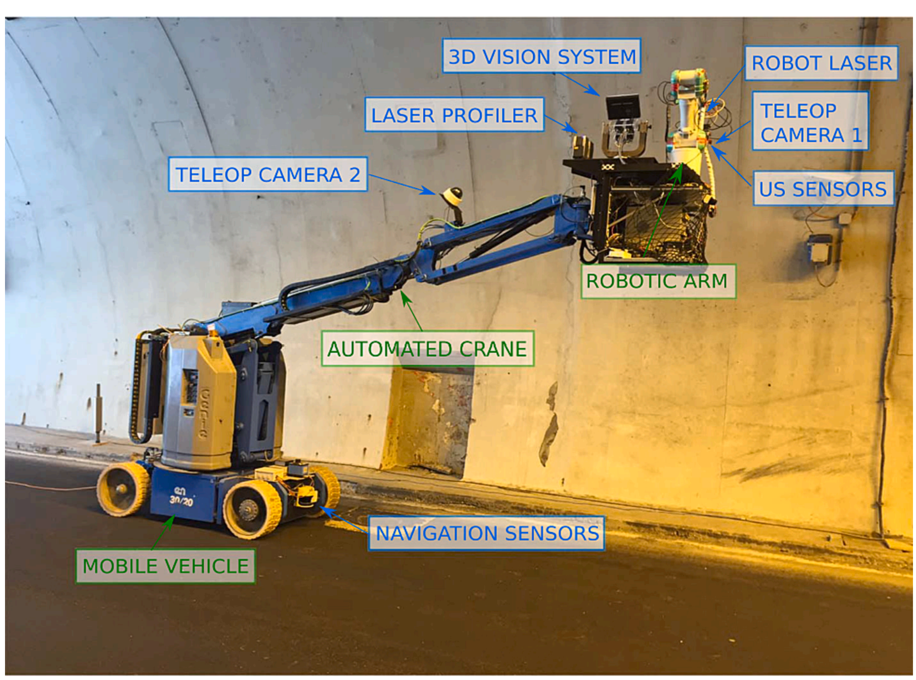


Fig. 24. ROBO-SPECT robotic system [222].

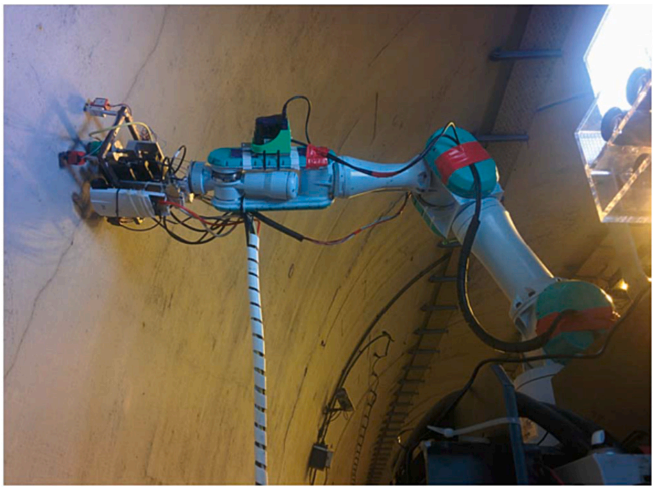


Fig. 25. Ultrasonic sensors touching a detected crack [222].

Fig. 26. Power Substation Inspection Robot [230].

corona detection cameras, and other test sensors, and control and communication units [230].

Zhang et al. [231] applied the immune ant colony algorithm and fuzzy neural network to the path planning and visual image post-processing of a substation inspection robot. The immune GA can effectively find the best walking path of the robot in the substation, and can effectively converge to the minimum path length [231]. A control optimization method for substation inspection robots based on an adaptive visual servo algorithm has been proposed to improve the accuracy of substation inspection robots capturing target images. The inspection robot can perform power equipment inspection tasks in the substation 24 h a day [232]. Zhang et al. [233] studied the heuristic search algorithm and Dijkstra algorithm and realized the path planning of a detection robot in the substation environment. Considering the actual operation of the system, the number of turns and the turning angle are added as evaluation indicators, and the Dijkstra algorithm is improved to make the algorithm more suitable for practical applications [233]. To realize the navigation path planning of a substation intelligent inspection robot, Zhan et al. [234] created a model based on the global path planning algorithm in turn based on the improved wolf pack algorithm, and finally planned the optimal path from the starting point through all the task points to the final destination [234].

6. Existing challenges and research prospects in civil engineering

Advances in the field of AGV/AMR over the past few decades have contributed greatly to the field of civil engineering. Existing research has successfully applied positioning, path planning, scheduling, navigation, and control to solve practical engineering problems in civil engineering, including detection, monitoring, construction, and repair. Although the applicability of AGV and AMR to solving complex engineering problems has been shown, many problems require research on how to further replace manual labor and improve the level of intelligence in practical applications.

6.1. Unmanned detection

In light of the need for automatic detection of pavement distress of pavements, bridge decks, bridge cables, bridge piers, and airport pavements, a distress detection robot system has been developed based on AGV/AMR technology combined with sensor fusion technology [235–237]. Through autonomous positioning, navigation, and task planning, the distress detection robot can realize full coverage detection in the designated detection operation area, automatically collect road surface image data and structural layer data, and provide high-quality and high-precision detection data for subsequent analysis [238–240].

In practical use, some necessary improvements in robot detection systems have also been found, including (1) The adaptability of existing task planning algorithms to complex curved roads needs to be improved. (2) The existing apparent detection modules based on area scan cameras have difficulty in identifying apparent disorders of spatial types such as misplacement and rutting. (3) The ability to overcome obstacles needs to be improved to ensure normal operation on bridge cables under poor working conditions. Therefore, future research will continue to improve the trajectory planning and navigation algorithms of detection robots and expand detection modules such as laser point clouds and 3-D cameras to further improve the adaptability and accuracy of systems for automatic distress detection.

6.2. Unmanned construction

AGV/AMR technology adopts sensor technology and signal processing technology, and integrates various onboard sensors such as vision and lidar to be applied to the construction field to realize unmanned construction, identify the environment and status of the construction site, and evaluate the acquired road information, vehicle location and obstacle information to make decisions and carry out construction operations [241–245].

The field of unmanned construction is currently limited by various constraints: (1) To accurately implement the collection of big data on construction, it is imperative to establish a unified digital data collection and storage standard or system. (2) Human-machine communication and machine-machine communication are limited by factors such as communication bandwidth and delay, construction cost, limited information exchange during construction, and poor real-time performance. (3)The computing power places high demands on the processor, and generally requires a quasi-desktop CPU or even a GPU, but AGV/AMR mostly uses embedded processors, which are difficult to expand on small AGV/AMR equipment in a short time.

6.3. Intelligent distress repair

Most existing distress repair systems rely on manpower, which is labor-intensive and the construction environment is harsh. Although semi-automatic repair equipment improves the construction environment and safety to a certain extent, the operator's field of vision in the cab is limited, even when surveillance video is used and it is also difficult to observe the repair process and effect the rational formulation of repair decisions [246,247]. Overall, the entire process of existing repair systems from distress identification to the end of the repair operation is inseparable from the intervention of human judgment and operating experience.

With the development of AGV/AMR technology, it is a research trend to apply this technology to distress repair in the field of civil engineering [248–251]. Intelligent distress repair should include image acquisition and display, crack detection, crack modeling, repair path planning, and action execution. Recognition accuracy and algorithm processing speed are two major problems which need to be studied.

7. Conclusions

This paper systematically reviews the technological development of AGVs and AMRs, focusing on their application in different scenarios in civil engineering. An in-depth review of papers in the field was conducted based on literature searches of several digital libraries. Based on these studies, the main research topic was determined to be the application of AGVs and AMRs in civil engineering, including detection, monitoring and construction.

To deal with the complex problems in this field, positioning, navigation, control, path planning and scheduling are applied to solve engineering problems in roads, bridges, tunnels and buildings. The benefits of AGVs and AMRs are: (1) saving human beings from dangerous environments and tedious work, (2) providing more standardized and objective inspections than humans, (3) improving construction quality in strict accordance with construction specifications, (4) promoting technological innovations in the civil engineering industry.

However, there are still limitations in the application of AGVs or AMRs, for the following reasons. (1) Limited by recognition and tracking accuracy and computing power, the capabilities of existing AGVs and AMRs are limited, (2) Insufficient data communication bandwidth and system real-time performance lead to the limited reliability of existing AGVs and AMRs, (3) The harsh environment of the civil engineering industry hinders testing and verification in AGV and AMR development.

In order to accelerate the application of AGVs/AMRs in civil engineering, the following recommendations are made: (1) develop a lightweight model-based deep convolutional neural network ensuring that it can run on embedded hardware, (2) further research on multi-sensor fusion of mobile robots to ensure that mobile robots can fully perceive environmental information and make optimal decisions to complete civil engineering operations, (3) further research methods based on SLAM algorithm should be used for accurate positioning and navigation of autonomous robots for construction tasks such as on-site inspection and object manipulation planning needs, (4) civil engineering operations often require the cooperation of multiple robots, requiring more efforts in multi-robot communication, intelligent sensing and robot motion control.

Declaration of Competing Interest

The authors do not have any conflict of interest with other entities or researchers.

Data availability

No data was used for the research described in the article.

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References

[1] Automatic Guided Vehicles. https://www.mhi.org/fundamentals/automatic-guided-vehicles, 2022.
[2] G. Ullrich, The History of Automated Guided Vehicle Systems, Automated Guided Vehicle Systems: A Primer with Practical Applications, 2015, pp. 1–14, https://doi.org/10.1007/978-3-662-44814-4_1.
[3] D. Nagarathinam, Current Status about Automated Guided Vehicle and Their Advantages and Application, 2020, https://doi.org/10.23883/IJRTER.2020.6007.AML85.
[4] O. Media, Application of TAICENN Embedded Computer ABOX-E7S in Security Patrol Robot. https://www.embeddedcomputing.com/application/industrial/automation-robotics/application-of-taicenn-embedded-computer-abox-e7s-in-security-patrol-robot, 2019.
[5] LANSINT. http://www.fjlxt.com/product_view_81_163.html, 2022.
[6] Interior of Warehouse in Logistic Center with Automated Guided. https://www.istockphoto.com/fr/photo/int%C3%A9rieur-de-lentrep%C3%B4t-dans-le-centre-logistique-avec-v%C3%A9hicule-guid%C3%A9-automatis%C3%A9-est-gm1192773352-339016463, 2022.
[7] I. Sota, Coronavirus: ¿puede un robot ayudar a proteger a los sanitarios que trabajan en primera línea?. https://elpais.com/elpais/2020/03/25/icon_design/1585140025_570156.html, 2020.
[8] S. Michael, B. Roger, Literature Review of Mobile Robots for Manufacturing, NIST Interagency/Internal Report (NISTIR), National Institute of Standards and Technology, Gaithersburg, MD, 2015, https://doi.org/10.6028/NIST.IR.8022.
[9] V. Murthy, Autonomous mobile robots designing, J. Glob. Res. Comput. Sci. 2 (2011). https://www.rroij.com/open-access/autonomous-mobile-robots-designing-126-129.pdf.
[10] M. Köseoğlu, O.M. Çelik, Ö. Pektaş, Design of an autonomous mobile robot based on ROS, International Artificial Intelligence and Data Processing Symposium (IDAP) 2017, IEEE, 2017, pp. 1–5, https://doi.org/10.1109/IDAP.2017.8090199.
[11] H. Sadruddin, A. Mahmoud, M. Atia, An indoor navigation system using stereo vision, IMU and UWB sensor fusion, IEEE Sens. 2019 (2019) 1–4, https://doi.org/10.1109/SENSORS43011.2019.8956942.
[12] C. Yuan, J. Liu, Y. Wang, Research on indoor positioning and navigation method of AGV based on multi-sensor fusion, highlights in science, Eng. Technol. 7 (2022) 206–213, https://doi.org/10.54097/hset.v7i.1060.
[13] X. Hu, Z. Luo, W. Jiang, AGV localization system based on ultra-wideband and vision guidance, Electronics 9 (2020) 448, https://doi.org/10.3390/electronics9030448.
[14] G. Ding, H. Lu, J. Bai, X. Qin, Development of a high precision UWB/vision-based AGV and control system, in: 2020 5th International Conference on Control and Robotics Engineering (ICCRE), 2020, pp. 99–103, https://doi.org/10.1109/ICCRE49379.2020.9096456.
[15] A. Masiero, C. Toth, J. Gabela, G. Retscher, A. Kealy, H. Perakis, V. Gikas, D. Grejner-Brzezinska, Experimental assessment of UWB and vision-based car cooperative positioning system, Remote Sens. 13 (2021) 4858, https://doi.org/10.3390/rs13234858.
[16] A.-T. Nguyen, V.-T. Nguyen, X.-T. Nguyen, C.-T. Vu, Development of a Multiple-Sensor Navigation System for Autonomous Guided Vehicle Localization, Springer Singapore, Singapore, 2021, pp. 402–410, https://doi.org/10.1007/978-981-16-2094-2_49.
[17] D. Song, G.M. Tian, J. Liu, Real-time localization measure and perception detection using multi-sensor fusion for Automated Guided Vehicles, in: 2021 40th Chinese Control Conference (CCC), 2021, pp. 3219–3224, https://doi.org/10.23919/CCC52363.2021.9550235.
[18] O. Sari, Sensor Fusion for Localization of Automated Guided Vehicles. https://aaltodoc.aalto.fi/bitstream/handle/123456789/47095/master_Sari_Onur_2020.pdf, 2020.
[19] M. Dares, K.W. Goh, Y.S. Koh, C.F. Yeong, E.L.M. Su, P.H. Tan, Automated Guided Vehicle Robot Localization with Sensor Fusion, Springer Nature Singapore, Singapore, 2022, pp. 135–143, https://doi.org/10.1007/978-981-16-8484-5_11.
[20] H. Che, G. Wang, C. Shi, A Multi-sensor Data Fusion Method Based on Improved XGBoost Model for AGV Localization, Springer Singapore, Singapore, 2021, pp. 602–610, https://doi.org/10.1007/978-981-16-2336-3_57.
[21] Q. Zou, Q. Sun, L. Chen, B. Nie, Q. Li, A comparative analysis of LiDAR SLAM-based indoor navigation for autonomous vehicles, IEEE Trans. Intell. Transp. Syst. 23 (2022) 6907–6921, https://doi.org/10.1109/TITS.2021.3063477.
[22] H. Ye, C. Zhou, A New EKF SLAM Algorithm of Lidar-Based AGV Fused with Bearing Information. https://briefs.techconnect.org/papers/a-new-ekf-slam-algorithm-of-lidar-based-agv-fused-with-bearing-information/, 2018.
[23] Y. Deng, Q. Liu, J. Bao, H. Sun, J. He, L. Lu, Terminal container automated guided vehicle based on Lidar navigation, SPIE Optic. Metrol. 11060 (2019), https://doi.org/10.1117/12.2526047.
[24] C. Ai, D. Geng, Z. Qi, L. Zheng, Z. Feng, Research on AGV navigation system based on binocular vision, in: 2021 IEEE International Conference on Real-time Computing and Robotics (RCAR), 2021, pp. 851–856, https://doi.org/10.1109/RCAR52367.2021.9517359.
[25] S. Liu, M. Xiong, W. Zhong, H. Xiong, Towards industrial scenario lane detection: vision-based AGV navigation methods, in: 2020 IEEE International Conference on Mechatronics and Automation (ICMA), 2020, pp. 1101–1106, https://doi.org/10.1109/ICMA49215.2020.9233837.

[26] T. Ji, L. Xie, Vision-aided localization and navigation for autonomous vehicles, in: 2022 IEEE 17th International Conference on Control & Automation (ICCA), 2022, pp. 599–604, https://doi.org/10.1109/ICCA54724.2022.9831868.

[27] G. Li, B. Zeng, W. Liao, X. Li, L. Gao, A new AGV scheduling algorithm based on harmony search for material transfer in a real-world manufacturing system, Adv. Mech. Eng. 10 (2018), https://doi.org/10.1177/1687814018765560, 1687814018765560.

[28] W.-Q. Zou, Q.-K. Pan, L. Wang, An effective multi-objective evolutionary algorithm for solving the AGV scheduling problem with pickup and delivery, Knowl.-Based Syst. 218 (2021), 106881, https://doi.org/10.1016/j.knosys.2021.106881.

[29] W. Han, J. Xu, Z. Sun, B. Liu, K. Zhang, Z. Zhang, X. Mei, Digital twin-based automated guided vehicle scheduling: a solution for its charging problems, Appl. Sci. 12 (2022) 3354, https://doi.org/10.3390/app12073354.

[30] M. Zhong, Y. Yang, Y. Dessouky, O. Postolache, Multi-AGV scheduling for conflict-free path planning in automated container terminals, Comput. Ind. Eng. 142 (2020), 106371, https://doi.org/10.1016/j.cie.2020.106371.

[31] Y. Liu, S. Ji, Z. Su, D. Guo, Multi-objective AGV scheduling in an automatic sorting system of an unmanned (intelligent) warehouse by using two adaptive genetic algorithms and a multi-adaptive genetic algorithm, PLoS One 14 (2019), e0226161, https://doi.org/10.1371/journal.pone.0226161.

[32] T. Zheng, Y. Xu, D. Zheng, AGV path planning based on improved A-star algorithm, in: 2019 IEEE 3rd Advanced Information Management, Communicates, Electronic and Automation Control Conference (IMCEC), 2019, pp. 1534–1538, https://doi.org/10.1109/IMCEC46724.2019.8983841.

[33] S. Ragothaman, M. Maaref, Z.M. Kassas, Autonomous ground vehicle Path Planning in urban environments using GNSS and cellular signals reliability maps: models and algorithms, IEEE Trans. Aerosp. Electron. Syst. 57 (2021) 1562–1580, https://doi.org/10.1109/TAES.2021.3054690.

[34] G. Tang, C. Tang, C. Claramunt, X. Hu, P. Zhou, Geometric A-star algorithm: an improved A-star algorithm for AGV path planning in a port environment, IEEE Access 9 (2021) 59196–59210, https://doi.org/10.1109/ACCESS.2021.3070054.

[35] T. Qiuyun, S. Hongyan, G. Hengwei, W. Ping, Improved particle swarm optimization algorithm for AGV path planning, IEEE Access 9 (2021) 33522–33531, https://doi.org/10.1109/ACCESS.2021.3061288.

[36] S. Li, J. Yan, L. Li, Automated guided vehicle: the direction of intelligent logistics, in: 2018 IEEE International Conference on Service Operations and Logistics, and Informatics (SOLI), 2018, pp. 250–255, https://doi.org/10.1109/SOLI.2018.8476726.

[37] R. Permana Saputra, E. Rijanto, Automatic Guided Vehicles System and Its Coordination Control for Containers Terminal Logistics Application, eprint arXiv: 2104.08331, 2021, https://doi.org/10.48550/arXiv.2104.08331.

[38] J. Stillig, N. Parspour, Novel Autonomous Guided Vehicle System for the Use in Logistics Applications, Springer, Berlin Heidelberg, Berlin, Heidelberg, 2021, pp. 424–432, https://doi.org/10.1007/978-3-662-62962-8_49.

[39] N. Tsolakis, D. Zissis, S. Papaefthimiou, N. Korfiatis, Towards AI driven environmental sustainability: an application of automated logistics in container port terminals, Int. J. Prod. Res. 60 (2022) 4508–4528, https://doi.org/10.1080/00207543.2021.1914355.

[40] H. Ding, Y. Huang, J. Shi, Q. Shi, Y. Yang, A novel industrial AGV control strategy based on dual-wheel chassis model, Assem. Autom. 42 (2022) 306–318, https://doi.org/10.1108/AA-09-2021-0122.

[41] A. Garcia-Rodriguez, J.G. Castillo-Garcia, H.G. Gonzalez-Hernandez, J.A. Reyes-Avendano, R.J. Mora-Salinas, Autonomous navigational system for an industrial AGV using ROS and ZED stereo camera, in: The 4th International Conference on Electronics, Communications and Control Engineering, Association for Computing Machinery, New York, NY, USA, 2021, pp. 117–122, https://doi.org/10.1145/3462676.3462695.

[42] R. Shreyas, B. Padmaja, H.B. Adithya, M.P. Sunil, Autonomous Ground Vehicle for Agricultural Applications, Springer International Publishing, Cham, 2019, pp. 200–206, https://doi.org/10.1007/978-3-030-03146-6_20.

[43] X. Gu, M.A. Khan, P. Angelov, B. Tiwary, E.S. Yourdshah, Z.X. Yang, A novel self-organizing PID approach for controlling mobile robot locomotion, in: 2020 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), 2020, pp. 1–10, https://doi.org/10.1109/FUZZ48607.2020.9177557.

[44] W.M.E. Mahgoub, I.M.H. Sanhoury, Adaptive navigation planner for autonomous locomotion control of nonholonomic wheeled mobile robot, in: 2018 International Conference on Computer, Control, Electrical, and Electronics Engineering (ICCCEEE), 2018, pp. 1–5, https://doi.org/10.1109/ICCCEEE.2018.8515856.

[45] I.-A. Maroşan, G. Constantin, Design of a modular locomotion system for autonomous mobile robots, MATEC Web Conf. 343 (2021) 08006, https://doi.org/10.1051/matecconf/202134308006.

[46] Machine learning for robot locomotion, Grounded simulation learning and adaptive planner parameter learning, in: 2021 IEEE International Conference on Big Data (Big Data), 2021, p. 6, https://doi.org/10.1109/BigData52589.2021.9671792.

[47] M. Cognetti, M. Aggravi, C. Pacchierotti, P. Salaris, P.R. Giordano, Perception-aware human-assisted navigation of mobile robots on persistent trajectories, IEEE Robot. Automat. Lett. 5 (2020) 4711–4718, https://doi.org/10.1109/LRA.2020.3003882.

[48] Q.M. Rahman, P. Corke, F. Dayoub, Run-time monitoring of machine learning for robotic perception: a survey of emerging trends, IEEE Access 9 (2021) 20067–20075, https://doi.org/10.1109/ACCESS.2021.3055015.

[49] A. Pandey, A.K. Kashyap, D.R. Parhi, B.K. Patle, Autonomous mobile robot navigation between static and dynamic obstacles using multiple ANFIS architecture, world, J. Eng. 16 (2019) 275–286, https://doi.org/10.1108/WJE-03-2018-0092.

[50] X. Ruan, D. Ren, X. Zhu, J. Huang, Mobile robot navigation based on deep reinforcement learning, in: 2019 Chinese Control And Decision Conference (CCDC), 2019, pp. 6174–6178, https://doi.org/10.1109/CCDC.2019.8832393.

[51] C. Huang, W. Zhang, Navigation control method of indoor mobile robot based on visual servo, Int. J. Antennas Propag. 2022 (2022), https://doi.org/10.1155/2022/6422841, 6422841.

[52] N.H. Singh, K. Thongam, Neural network-based approaches for mobile robot navigation in static and moving obstacles environments, Intell. Serv. Robot. 12 (2019) 55–67, https://doi.org/10.1007/s11370-018-0260-2.

[53] S. Gatesichapakorn, J. Takamatsu, M. Ruchanurucks, ROS based autonomous mobile robot navigation using 2D LiDAR and RGB-D camera, in: 2019 First International Symposium on Instrumentation, Control, Artificial Intelligence, and Robotics (ICA-SYMP), 2019, pp. 151–154, https://doi.org/10.1109/ICA-SYMP.2019.8645984.

[54] D. Bore, A. Rana, N. Kolhare, U. Shinde, Automated guided vehicle using robot operating systems, in: 2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI), 2019, pp. 819–822, https://doi.org/10.1109/ICOEI.2019.8862716.

[55] F. Okumuş, A.F. Kocamaz, Cloud based indoor navigation for ROS-enabled automated guided vehicles, in: 2019 International Artificial Intelligence and Data Processing Symposium (IDAP), 2019, pp. 1–4, https://doi.org/10.1109/IDAP.2019.8875993.

[56] Worker Shortages in Manufacturing Make AGVs More Beneficial Than Ever. https://www.fredagv.com/news/worker-shortages-in-manufacturing-make-agvs-more-beneficial-than-ever/, 2022.

[57] G. Ullrich, T. Albrecht, Geschichte der Fahrerlosen Transportsysteme, in: Fahrerlose Transportsysteme: Eine Fibel – mit Praxisanwendungen – zur Technik – für die Planung, 2019, pp. 1–28, https://doi.org/10.1007/978-3-658-27472-6_1.

[58] Epochale FTS-Entwicklung, Ein Bericht aus dem Forum-FTS von Dr.-Ing. Günter Ullrich, VDI - PDF Free Download. https://docplayer.org/131739072-Epochale-fts-entwicklung-ein-bericht-aus-dem-forum-fts-von-dr-ing-guenter-ullrich-vdi.html, 2022.

[59] J. Borenstein, Experimental results from internal odometry error correction with the OmniMate mobile robot, IEEE Trans. Robot. Autom. 14 (1998) 963–969, https://doi.org/10.1109/70.736779.

[60] AUTOMATED, GUIDED VEHICLES AGVs for Industry, Healthcare, Logistics and Process Automation by Ek Robotics. https://www.expo21xx.com/industry4/15335_st3_iot_automation_machine/default.htm, 2022.

[61] G. Ullrich, Automated Guided Vehicle Systems, Springer, Berlin, Heidelberg, 2015, pp. 973–978, https://doi.org/10.1007/978-3-662-44814-4.

[62] AGV Robot | EVO roller 2. https://www.oppent-evo.com/en/prodotto/evo-roller-2-2/, 2022.

[63] M. Indri, L. Lachello, I. Lazzero, F. Sibona, S. Trapani, Smart sensors applications for a new paradigm of a production line, Sensors 19 (2019) 650, https://doi.org/10.3390/s19030650.

[64] B.L. Burks, G.D. Saussure, C.R. Weisbin, J.P. Jones, W.R. Hamel, Autonomous navigation, exploration, and recognition using the HERMIES-IIB robot, IEEE Expert 2 (1987) 18–27, https://doi.org/10.1109/MEX.1987.5006527.

[65] Fig. 2.12-Le Robot Mobile Hilare 2 bis muni du bras GT6A. https://www.researchgate.net/figure/Le-robot-mobile-Hilare-2-bis-muni-du-bras-GT6A_fig9_281416197, 2022.

[66] Jido. https://www.laas.fr/robots/jido/data/en/robot.php, 2022.

[67] A. Sharp, K. Kruusamäe, B. Ebersole, M. Pryor, Semiautonomous dual-arm mobile manipulator system with intuitive supervisory user interfaces, in: 2017 IEEE Workshop on Advanced Robotics and its Social Impacts (ARSO), 2017, pp. 1–6, https://doi.org/10.1109/ARSO.2017.8025195.

[68] ANYmal on Wheels. https://rsl.ethz.ch/robots-media/anymal-wheels.html, 2022.

[69] Z. Zhou, Q. Zhi, S. Morisaki, S. Yamamoto, A systematic literature review on enterprise architecture visualization methodologies, IEEE Access 8 (2020) 96404–96427, https://doi.org/10.1109/ACCESS.2020.2995850.

[70] M.R. Belgaum, S. Musa, M.M. Alam, M.M. Su'ud, A systematic review of load balancing techniques in software-defined networking, IEEE Access 8 (2020) 98612–98636, https://doi.org/10.1109/ACCESS.2020.2995849.

[71] C. Kirsch, C. Röhrig, Global localization and position tracking of an automated guided vehicle, IFAC Proc. Vol. 44 (2011) 14036–14041, https://doi.org/10.3182/20110828-6-IT-1002.01245.

[72] S. Kim, H. Jin, M. Seo, D. Har, Optimal path planning of automated guided vehicle using dijkstra algorithm under dynamic conditions, in: 2019 7th International Conference on Robot Intelligence Technology and Applications (RiTA), 2019, pp. 231–236, https://doi.org/10.1109/RITAPP.2019.8932804.

[73] Y. Zhou, J. Gao, Y. Zhang, H. Wu, The route planning for AMR based on combined ant colony and genetic algorithm, in: 2019 Chinese Control And Decision Conference (CCDC), 2019, pp. 4560–4565, https://doi.org/10.1109/CCDC.2019.8832733.

[74] H.-Y. Zhang, W.-M. Lin, A.-X. Chen, Path planning for the mobile robot: a review, Symmetry 10 (2018) 450, https://doi.org/10.3390/sym10100450.

[75] M.-S. Wang, S.-C. Chen, P.-H. Chuang, S.-Y. Wu, F.-S. Hsu, Neural network control-based drive design of servomotor and its application to automatic guided vehicle, Math. Probl. Eng. 2015 (2015), 612932, https://doi.org/10.1155/2015/612932.

[76] S. Cebollada, L. Payá, D. Valiente, X. Jiang, Ó. Reinoso, An evaluation between global appearance descriptors based on analytic methods and deep learning techniques for localization in autonomous mobile robots, in: 16th International

Conference on Informatics in Control, Automation and Robotics, 2019, pp. 284–291, https://doi.org/10.5220/0007837102840291.
[77] S. Erfani, A. Jafari, A. Hajiahmad, Comparison of two data fusion methods for localization of wheeled mobile robot in farm conditions, Artif. Intellig. Agric. 1 (2019) 48–55, https://doi.org/10.1016/j.aiia.2019.05.002.
[78] P. Weinzaepfel, G. Csurka, Y. Cabon, M. Humenberger, Visual localization by learning objects-of-interest dense match regression, in: 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2019, pp. 5627–5636, https://doi.org/10.1109/CVPR.2019.00578.
[79] G. Zhou, J. Luo, S. Xu, S. Zhang, S. Meng, K. Xiang, An EKF-based multiple data fusion for mobile robot indoor localization, Assem. Autom. 41 (2021) 274–282, https://doi.org/10.1108/AA-12-2020-0199.
[80] S. Bakshi, T. Feng, Z. Yan, D. Chen, Fast scheduling of autonomous mobile robots under task space constraints with priorities, J. Dyn. Syst. Meas. Control. 141 (2019), https://doi.org/10.1115/1.4043116.
[81] L. Chang, L. Shan, C. Jiang, Y. Dai, Reinforcement based mobile robot path planning with improved dynamic window approach in unknown environment, Auton. Robot. 45 (2021) 51–76, https://doi.org/10.1007/s10514-020-09947-4.
[82] H. Xu, S. Zhang, P. Cao, J. Qin, C. Wang, A research on AGV integrated navigation system based on fuzzy PID adaptive Kalman filter, in: 2019 IEEE 3rd Advanced Information Management, Communicates, Electronic and Automation Control Conference (IMCEC), 2019, pp. 482–486, https://doi.org/10.1109/IMCEC46724.2019.8983891.
[83] P.M. Blok, K. van Boheemen, F.K. van Evert, J. Ijsselmuiden, G.-H. Kim, Robot navigation in orchards with localization based on particle filter and Kalman filter, Comput. Electron. Agric. 157 (2019) 261–269, https://doi.org/10.1016/j.compag.2018.12.046.
[84] Y. Chen, Y. Wu, H. Xing, A complete solution for AGV SLAM integrated with navigation in modern warehouse environment, in: 2017 Chinese Automation Congress (CAC), 2017, pp. 6418–6423, https://doi.org/10.1109/CAC.2017.8243934.
[85] X. Lai, G. Zhu, J. Chambers, A fuzzy adaptive extended Kalman filter exploiting the student's t distribution for mobile robot tracking, Meas. Sci. Technol. 32 (2021), 105017, https://doi.org/10.1088/1361-6501/ac0ca9.
[86] A.S.R. Silvirianti, A. Krisna, S. Rusdinar, R. Yuwono, Nugraha, speed control system design using fuzzy-pid for load variation of automated guided vehicle (AGV), in: 2017 2nd International Conference on Frontiers of Sensors Technologies (ICFST), 2017, pp. 426–430, https://doi.org/10.1109/ICFST.2017.8210549.
[87] M.R. Azizi, A. Rastegarpanah, R. Stolkin, Motion planning and control of an omnidirectional mobile robot in dynamic environments, Robotics 10 (2021) 48, https://doi.org/10.3390/robotics10010048.
[88] W. Chun-Fu, W. Xiao-Long, C. Qing-Xie, C. Xiao-Wei, L. Guo-Dong, Research on visual navigation algorithm of AGV used in the small agile warehouse, in: 2017 Chinese Automation Congress (CAC), 2017, pp. 217–222, https://doi.org/10.1109/CAC.2017.8242766.
[89] P. Karpyshev, V. Ilin, I. Kalinov, A. Petrovsky, D. Tsetserukou, Autonomous mobile robot for apple plant disease detection based on CNN and multi-spectral vision system, in: 2021 IEEE/SICE International Symposium on System Integration (SII), 2021, pp. 157–162, https://doi.org/10.1109/IEEECONF49454.2021.9382649.
[90] S. Zhou, G. Cheng, Q. Meng, H. Lin, Z. Du, F. Wang, Development of multi-sensor information fusion and AGV navigation system, in: 2020 IEEE 4th Information Technology, Networking, Electronic and Automation Control Conference (ITNEC), 2020, pp. 2043–2046, https://doi.org/10.1109/ITNEC48623.2020.9084687.
[91] X. Chen, W. Lin, J. Liu, L. Guan, Y. Zheng, F. Gao, Electromagnetic Guided Factory Intelligent AGV, Atlantis Press, 2016, pp. 200–205, https://doi.org/10.2991/icmit-16.2016.36.
[92] R.-S. Run, Z.-Y. Xiao, Indoor autonomous vehicle navigation—a feasibility study based on infrared technology, Appl. Syst. Innov. 1 (2018) 4, https://doi.org/10.3390/asi1010004.
[93] L. Lynch, T. Newe, J. Clifford, J. Coleman, J. Walsh, D. Toal, Automated ground vehicle (AGV) and sensor technologies - a review, in: 2018 12th International Conference on Sensing Technology (ICST), 2018, pp. 347–352, https://doi.org/10.1109/ICSensT.2018.8603640.
[94] J. Kim, S. Woo, J. Kim, J. Do, S. Kim, S. Bae, Inertial navigation system for an automatic guided vehicle with Mecanum wheels, Int. J. Precis. Eng. Manuf. 13 (2012) 379–386, https://doi.org/10.1007/s12541-012-0048-9.
[95] E. Pivarčiová, P. Božek, Y. Turygin, I. Zajačko, A. Shchenyatsky, Š. Václav, M. Císar, B. Gemela, Analysis of control and correction options of mobile robot trajectory by an inertial navigation system, Int. J. Adv. Robot. Syst. 15 (2018), https://doi.org/10.1177/1729881418755165, 1729881418755165.
[96] T. Bui, P. Doan, S. Park, H.-K. Kim, S. Kim, AGV trajectory control based on laser sensor navigation, Int. J. Sci. Eng. 4 (2012), https://doi.org/10.12777/ijse.4.1.16-20.
[97] T. Ran, L. Yuan, J.B. Zhang, Scene perception based visual navigation of mobile robot in indoor environment, ISA Trans. 109 (2021) 389–400, https://doi.org/10.1016/j.isatra.2020.10.023.
[98] Y.D.V. Yasuda, L.E.G. Martins, F.A.M. Cappabianco, Autonomous visual navigation for mobile robots: a systematic literature review, ACM Comput. Surv. 53 (2020) 1–34, https://doi.org/10.1145/3368961.
[99] R. Siegwart, I. Nourbakhsh, D. Scaramuzza, Introduction to Autonomous Mobile Robots, second edition, MIT Press, 2011. https://www.academia.edu/3491049/Intro_to_Autonomous_Mobile_Robots?bulkDownload=thisPaper-topRelated-sameAuthor-citingThis-citedByThis-secondOrderCitations&from=cover_page.
[100] K. Danica, V. Markus, Vision for Robotics, Foundations and Trends in Robotics 1, 2009, pp. 1–78, https://doi.org/10.1561/2300000001.
[101] M. Hao, An autonomous navigation algorithm for monocular visual recognition, in: 2020 IEEE 4th Information Technology, Networking, Electronic and Automation Control Conference (ITNEC), 2020, pp. 1975–1978, https://doi.org/10.1109/ITNEC48623.2020.9084916.
[102] D. Fu, H. Xia, Y. Qiao, Monocular visual-inertial navigation for dynamic environment, Remote Sens. 13 (2021) 1610, https://doi.org/10.3390/rs13091610.
[103] G. Kovacs, Y. Kunii, T. Maeda, H. Hashimoto, Trajectory estimation and position correction for hopping robot navigation using monocular camera, ROBOMECH J. 7 (2020) 25, https://doi.org/10.1186/s40648-020-00172-3.
[104] R. Miyamoto, M. Adachi, H. Ishida, T. Watanabe, K. Matsutani, H. Komatsuzaki, S. Sakata, R. Yokota, S. Kobayashi, Visual navigation based on semantic segmentation using only a monocular camera as an external sensor, J. Robot. Mechatron. 32 (2020) 1137–1153, https://doi.org/10.20965/jrm.2020.p1137.
[105] T. Sun, Y. Liu, Y. Wang, Z. Xiao, An improved monocular visual-inertial navigation system, IEEE Sensors J. 21 (2021) 11728–11739, https://doi.org/10.1109/JSEN.2020.3022783.
[106] H.W. Chae, J.H. Choi, J.B. Song, Robust and autonomous stereo visual-inertial navigation for non-holonomic mobile robots, IEEE Trans. Veh. Technol. 69 (2020) 9613–9623, https://doi.org/10.1109/TVT.2020.3004163.
[107] L. Cheng, Y. Dai, R. Peng, X. Nong, Positioning and navigation of mobile robot with asynchronous fusion of binocular vision system and inertial navigation system, Int. J. Adv. Robot. Syst. 14 (2017), https://doi.org/10.1177/1729881417745607, 1729881417745607.
[108] T.S. Sheikh, I.M. Afanasyev, Stereo Vision-Based Optimal Path Planning with Stochastic Maps for Mobile Robot Navigation, Intelligent Autonomous Systems 15, Springer International Publishing, Cham, 2019, pp. 40–55, https://doi.org/10.1007/978-3-030-01370-7_4.
[109] Q. Zhao, B. Zhang, S. Lyu, H. Zhang, D. Sun, G. Li, W. Feng, A CNN-SIFT hybrid pedestrian navigation method based on first-person vision, Remote Sens. 10 (2018) 1229, https://doi.org/10.3390/rs10081229.
[110] S. Sadeghi Esfahlani, A. Sanaei, M. Ghorabian, H. Shirvani, The deep convolutional neural network role in the autonomous navigation of mobile robots (SROBO), Remote Sens. 14 (2022) 3324, https://doi.org/10.3390/rs14143324.
[111] L. Tai, S. Li, M. Liu, A deep-network solution towards model-less obstacle avoidance, in: 2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2016, pp. 2759–2764, https://doi.org/10.1109/IROS.2016.7759428.
[112] Z. Machkour, D. Ortiz-Arroyo, P. Durdevic, Classical and deep learning based visual Servoing systems: a survey on state of the art, J. Intell. Robot. Syst. 104 (2021) 11, https://doi.org/10.1007/s10846-021-01540-w.
[113] A. Ahmadi, L. Nardi, N. Chebrolu, C. Stachniss, Visual servoing-based navigation for monitoring row-crop fields, in: 2020 IEEE International Conference on Robotics and Automation (ICRA), 2020, pp. 4920–4926, https://doi.org/10.1109/ICRA40945.2020.9197114.
[114] K. Wang, Y. Liu, L. Li, Visual servoing trajectory tracking of nonholonomic mobile robots without direct position measurement, IEEE Trans. Robot. 30 (2014) 1026–1035, https://doi.org/10.1109/TRO.2014.2317891.
[115] A. Lee, S. Levine, P. Abbeel, Learning visual servoing with deep features and fitted Q-iteration, ICLR 2017 (2017), https://doi.org/10.48550/arXiv.1703.11000.
[116] H. Lee, J. Park, W. Chung, Localization of outdoor mobile robots using curb features in urban road environments, Math. Probl. Eng. 2014 (2014), 368961, https://doi.org/10.1155/2014/368961.
[117] L. Zhao, C. Ye, Y. Zhang, X. Xu, J. Chen, Path recognition method of robot vision navigation in unstructured environments, Acta Opt. Sin. 38 (2018) 0815028, https://doi.org/10.3788/aos201838.0815028.
[118] J. Zhang, Q. Xu, Research on robot's road detection technology based on machine vision, in: AIAM 2019: Proceedings of the 2019 International Conference on Artificial Intelligence and Advanced Manufacturing, 2019, pp. 1–4, https://doi.org/10.1145/3358331.3358362.
[119] Q. Zhu, Y. Han, P. Liu, Y. Xiao, P. Lu, C. Cai, Motion planning of autonomous mobile robot using recurrent fuzzy neural network trained by extended Kalman filter, Computat. Intellig. Neurosci. 2019 (2019) 1934575, https://doi.org/10.1155/2019/1934575.
[120] Y. Raaj, A. John, T. Jin, 3D object localization using forward looking sonar (FLS) and optical camera via particle filter based calibration and fusion, in: OCEANS 2016 MTS/IEEE Monterey, 2016, pp. 1–10, https://doi.org/10.1109/OCEANS.2016.7761077.
[121] S.W. Yang, C.C. Wang, On solving mirror reflection in LIDAR sensing, IEEE/ASME Trans. Mech. 16 (2011) 255–265, https://doi.org/10.1109/TMECH.2010.2040113.
[122] S. Soleimanpour, S.S. Ghidary, K. Meshgi, Sensor fusion in robot localization using DS-evidence theory with conflict detection using Mahalanobis distance, in: 2008 7th IEEE International Conference on Cybernetic Intelligent Systems, 2008, pp. 1–6, https://doi.org/10.1109/UKRICIS.2008.4798964.
[123] G. Ligorio, A.M. Sabatini, Extended Kalman filter-based methods for pose estimation using visual, inertial and magnetic sensors: comparative analysis and performance evaluation, Sensors 13 (2013) 1919–1941, https://doi.org/10.3390/s130201919.
[124] M.M. Shaikh, W. Bahn, C. Lee, T.I. Kim, T.J. Lee, K.S. Kim, D. Cho, Mobile robot vision tracking system using Unscented Kalman Filter, in: 2011 IEEE/SICE International Symposium on System Integration (SII), 2011, pp. 1214–1219, https://doi.org/10.1109/SII.2011.6147622.

[125] P. Gemeiner, P. Einramhof, M. Vincze, Simultaneous motion and structure estimation by fusion of inertial and vision data, Int. J. Robot. Res. 26 (2007) 591–605, https://doi.org/10.1177/0278364907080058.
[126] Z. Mikulová, F. Duchoň, M. Dekan, A. Babinec, Localization of mobile robot using visual system, Int. J. Adv. Robot. Syst. 14 (2017), https://doi.org/10.1177/1729881417736085, 1729881417736085.
[127] R. Mur-Artal, J.M.M. Montiel, J.D. Tardós, ORB-SLAM: a versatile and accurate monocular SLAM system, IEEE Trans. Robot. 31 (2015) 1147–1163, https://doi.org/10.1109/TRO.2015.2463671.
[128] R. Mur-Artal, J.D. Tardós, ORB-SLAM2: an open-source SLAM system for monocular, stereo, and RGB-D cameras, IEEE Trans. Robot. 33 (2017) 1255–1262, https://doi.org/10.1109/TRO.2017.2705103.
[129] D. Vivet, A. Debord, G. Pages, PAVO: a parallax based bi-monocular VO approach for autonomous navigation in various environments, in: Proceedings of the DISP Conference, St Hugh College, Oxford, UK, 2019, pp. 1–7. https://www.semanticscholar.org/paper/PAVO%3A-a-Parallax-based-Bi-Monocular-VO-Approach-For-Vivet-Debord/aa3bef6e1bab7092219b23e242b78f61d3b18467.
[130] B. Siciliano, O. Khatib, Robotics and the Handbook, Springer Handbook of Robotics, 2016, pp. 1–6, https://doi.org/10.1007/978-3-319-32552-1_1.
[131] J. Engel, V. Koltun, D. Cremers, Direct sparse odometry, IEEE Trans. Pattern Anal. Mach. Intell. 40 (2018) 611–625, https://doi.org/10.1109/TPAMI.2017.2658577.
[132] J. Engel, T. Schöps, D. Cremers, LSD-SLAM: Large-Scale Direct Monocular SLAM, Springer International Publishing, Cham, 2014, pp. 834–849, https://doi.org/10.1007/978-3-319-10605-2_54.
[133] R.A. Newcombe, S.J. Lovegrove, A.J. Davison, DTAM: dense tracking and mapping in real-time, in: 2011 International Conference on Computer Vision, 2011, pp. 2320–2327, https://doi.org/10.1109/ICCV.2011.6126513.
[134] R.A. Newcombe, S. Izadi, O. Hilliges, D. Molyneaux, D. Kim, A.J. Davison, P. Kohi, J. Shotton, S. Hodges, A. Fitzgibbon, KinectFusion: real-time dense surface mapping and tracking, in: 2011 10th IEEE International Symposium on Mixed and Augmented Reality, 2011, pp. 127–136, https://doi.org/10.1109/ISMAR.2011.6092378.
[135] W. Thomas, M. John, K. Michael, F. Maurice, J. Hordur, J.L. John, Kintinuous: spatially extended kinectfusion, in: Proceedings of RSS '12 Workshop on RGB-D: Advanced Reasoning with Depth Cameras, 2012. http://hdl.handle.net/1721.1/71756.
[136] T. Schöps, T. Sattler, M. Pollefeys, BAD SLAM: bundle adjusted direct RGB-D SLAM, in: 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2019, pp. 134–144, https://doi.org/10.1109/CVPR.2019.00022.
[137] Z. Zhang, Microsoft kinect sensor and its effect, IEEE Multim. 19 (2012) 4–10, https://doi.org/10.1109/MMUL.2012.24.
[138] R.F. Salas-Moreno, B. Glocken, P.H.J. Kelly, A.J. Davison, Dense planar SLAM, in: 2014 IEEE International Symposium on Mixed and Augmented Reality (ISMAR), 2014, pp. 157–164, https://doi.org/10.1109/ISMAR.2014.6948422.
[139] K. Tateno, F. Tombari, N. Navab, When 2.5D is not enough: simultaneous reconstruction, segmentation and recognition on dense SLAM, in: 2016 IEEE International Conference on Robotics and Automation (ICRA), 2016, pp. 2295–2302, https://doi.org/10.1109/ICRA.2016.7487378.
[140] H. Kim, S. Leutenegger, A.J. Davison, Real-Time 3D Reconstruction and 6-DoF Tracking with an Event Camera, Springer International Publishing, Cham, 2016, pp. 349–364, https://doi.org/10.1007/978-3-319-46466-4_21.
[141] D. Weikersdorfer, D.B. Adrian, D. Cremers, J. Conradt, Event-based 3D SLAM with a depth-augmented dynamic vision sensor, in: 2014 IEEE International Conference on Robotics and Automation (ICRA), 2014, pp. 359–364, https://doi.org/10.1109/ICRA.2014.6906882.
[142] X. Yang, J. Guan, L. Ding, Z. You, V.C.S. Lee, M.R. Mohd Hasan, X. Cheng, Research and applications of artificial neural network in pavement engineering: a state-of-the-art review, J. Traffic Transp. Eng. (Engl. Ed.) 8 (2021) 1000–1021, https://doi.org/10.1016/j.jtte.2021.03.005.
[143] J. Liu, X. Yang, S. Lau, X. Wang, S. Luo, V.C.-S. Lee, L. Ding, Automated pavement crack detection and segmentation based on two-step convolutional neural network, Comput. -Aided Civil Infrastruct. Eng. 35 (2020) 1291–1305, https://doi.org/10.1111/mice.12622.
[144] J. Guan, X. Yang, L. Ding, X. Cheng, V.C.S. Lee, C. Jin, Automated pixel-level pavement distress detection based on stereo vision and deep learning, Autom. Constr. 129 (2021), 103788, https://doi.org/10.1016/j.autcon.2021.103788.
[145] L.V. Nguyen, S. Gibb, H.X. Pham, H.M. La, A mobile robot for automated civil infrastructure inspection and evaluation, in: 2018 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR), 2018, pp. 1–6, https://doi.org/10.1109/SSRR.2018.8468642.
[146] N. Gucunski, J. Kim, K. Dinh, T. Duong, R. Zobel, Similarities and Differences in Condition Assessment of Concrete Bridge Decks by Visual Inspection and NDE, NDE/NDT for Highways & Bridges: SMT 2016, Portland, Oregon, 2016, pp. 58–64. https://ndtlibrary.asnt.org/2016/SimilaritiesandDifferencesinConditionAssessmentofConcreteBridgeDecksbyVisualInspectionandNDE.
[147] H.M. La, R.S. Lim, B.B. Basily, N. Gucunski, J. Yi, A. Maher, F.A. Romero, H. Parvardeh, Mechatronic systems design for an autonomous robotic system for high-efficiency bridge deck inspection and evaluation, IEEE/ASME Trans. Mech. 18 (2013) 1655–1664, https://doi.org/10.1109/TMECH.2013.2279751.
[148] N. Nguyen, K. Krishnakumar, J. Kaneshige, P. Nespeca, Dynamics and adaptive control for stability recovery of damaged asymmetric aircraft, in: AIAA Guidance, Navigation, and Control Conference and Exhibit, 2012, https://doi.org/10.2514/6.2006-6049.
[149] N. Nguyen, K. Krishnakumar, J. Kaneshige, P. Nespeca, Flight dynamics and hybrid adaptive control of damaged aircraft, J. Guid. Control. Dyn. 31 (2008) 751–764, https://doi.org/10.2514/1.28142.
[150] L. Yi, L. Zou, M. Sato, Practical approach for high-resolution airport pavement inspection with the Yakumo multistatic array ground-penetrating radar system, Sensors 18 (2018) 2684, https://doi.org/10.3390/s18082684.
[151] A. Jamshidi, K. Kurumisawa, T. Nawa, M.O. Hamzah, Analysis of structural performance and sustainability of airport concrete pavements incorporating blast furnace slag, J. Clean. Prod. 90 (2015) 195–210, https://doi.org/10.1016/j.jclepro.2014.11.046.
[152] G. Sollazzo, T.F. Fwa, G. Bosurgi, An ANN model to correlate roughness and structural performance in asphalt pavements, Constr. Build. Mater. 134 (2017) 684–693, https://doi.org/10.1016/j.conbuildmat.2016.12.186.
[153] Z. Gui, H. Li, Automated defect detection and visualization for the robotic airport runway inspection, IEEE Access 8 (2020) 76100–76107, https://doi.org/10.1109/ACCESS.2020.2986483.
[154] D. Lattanzi, G. Miller, Review of robotic infrastructure inspection systems, J. Infrastruct. Syst. 23 (2017), https://doi.org/10.1061/(ASCE)IS.1943-555X.0000353, 04017004.
[155] Z. Gui, X. Zhong, Y. Wang, T. Xiao, Y. Deng, H. Yang, R. Yang, A cloud-edge-terminal-based robotic system for airport runway inspection, Ind. Robot. 48 (2021) 846–855, https://doi.org/10.1108/IR-01-2021-0004.
[156] Y. Chen, Y. Dai, Y. Liu, Design & implementation of airport runway robot based on artificial intelligence, in: 2021 IEEE 5th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC), 2021, pp. 2636–2640, https://doi.org/10.1109/IAEAC50856.2021.9390864.
[157] H. Cai, T. Kuczek, P.S. Dunston, S. Li, Correlating intelligent compaction data to in situ soil compaction quality measurements, J. Constr. Eng. Manag. 143 (2017), https://doi.org/10.1061/(ASCE)CO.1943-7862.0001333, 04017038.
[158] X. Zhu, S. Bai, G. Xue, J. Yang, Y. Cai, W. Hu, X. Jia, B. Huang, Assessment of compaction quality of multi-layer pavement structure based on intelligent compaction technology, Constr. Build. Mater. 161 (2018) 316–329, https://doi.org/10.1016/j.conbuildmat.2017.11.139.
[159] D. Liu, Y. Wang, J. Chen, Y. Zhang, Intelligent compaction practice and development: a bibliometric analysis, Eng. Constr. Archit. Manag. 27 (2020) 1213–1232, https://doi.org/10.1108/ECAM-05-2019-0252.
[160] L. Lu, F. Dai, J.P. Zaniewski, Automatic roller path tracking and mapping for pavement compaction using infrared thermography, Comput. -Aided Civil Infrastruct. Eng. 36 (2021) 1416–1434, https://doi.org/10.1111/mice.12683.
[161] A. Dude, Basic Principles of Asphalt Compaction Compaction Methods Compaction Equipment Rolling Technique. https://www.academia.edu/40193675/Basic_Principles_of_Asphalt_Compaction_Compaction_methods_Compaction_equipment_Rolling_technique, 2009.
[162] A.V. Le, P.-C. Ku, T. Than Tun, N. Huu Khanh Nhan, Y. Shi, R.E. Mohan, Realization energy optimization of complete path planning in differential drive based self-reconfigurable floor cleaning robot, Energies 12 (2019) 1136, https://doi.org/10.3390/en12061136.
[163] A.V. Le, N.H.K. Nhan, R.E. Mohan, Evolutionary algorithm-based complete coverage path planning for tetriamond tiling robots, Sensors 20 (2020) 445, https://doi.org/10.3390/s20020445.
[164] A.V. Le, V. Prabakaran, V. Sivanantham, R.E. Mohan, Modified A-star algorithm for efficient coverage path planning in tetris inspired self-reconfigurable robot with integrated laser sensor, Sensors 18 (2018) 2585, https://doi.org/10.3390/s18082585.
[165] B. Ramalingam, A.K. Lakshmanan, M. Ilyas, A.V. Le, M.R. Elara, Cascaded machine-learning technique for debris classification in floor-cleaning robot application, Appl. Sci. 8 (2018) 2649, https://doi.org/10.3390/app8122649.
[166] A.V. Le, A.A. Hayat, M.R. Elara, N.H.K. Nhan, K. Prathap, Reconfigurable pavement sweeping robot and pedestrian cohabitant framework by vision techniques, IEEE Access 7 (2019) 159402–159414, https://doi.org/10.1109/ACCESS.2019.2950675.
[167] M.A.V.J. Muthugala, A.V. Le, E.S. Cruz, M. Rajesh Elara, P. Veerajagadheswar, M. Kumar, A self-organizing fuzzy logic classifier for benchmarking robot-aided blasting of ship hulls, Sensors 20 (2020) 3215, https://doi.org/10.3390/s20113215.
[168] A. Krishna Lakshmanan, R. Elara Mohan, B. Ramalingam, A. Vu Le, P. Veerajagadeshwar, K. Tiwari, M. Ilyas, Complete coverage path planning using reinforcement learning for Tetromino based cleaning and maintenance robot, Autom. Constr. 112 (2020) 103078, https://doi.org/10.1016/j.autcon.2020.103078.
[169] N. Tan, N. Rojas, R. Elara Mohan, V. Kee, R. Sosa, Nested reconfigurable robots: theory, design, and realization, Int. J. Adv. Robot. Syst. 12 (2015) 110, https://doi.org/10.5772/60507.
[170] Dream Robotic Suction Sweeper | Singapore Supersteam. http://www.supersteam.com.sg/products/cleaning-machines/dream-robotic-suction-sweeper, 2022.
[171] Mingnuo - Mamut - Industrial Vacuum Cleaner by Nantong, Mingnuo Electric Technology Co., Ltd, 2022. https://www.environmental-expert.com/products/mingnuo-model-mamut-industrial-vacuum-cleaner-553425.
[172] Green Machines Compact Air Sweeper. https://tcs-slovakia.sk/wp-content/uploads/2017/11/tennant636-brochure-en.pdf, 2017.
[173] Compact Road Sweepers. https://www.johnstonsweepers.com/wp-content/uploads/2017/12/cn101-brochure-78115.pdf, 2019.
[174] L. Yi, A.V. Le, A.A. Hayat, C.S.C.S. Borusu, R.E. Mohan, N.H.K. Nhan, P. Kandasamy, Reconfiguration during locomotion by pavement sweeping robot with feedback control from vision system, IEEE Access 8 (2020) 113355–113370, https://doi.org/10.1109/ACCESS.2020.3003376.

[175] A.A. Hayat, R. Parween, M.R. Elara, K. Parsuraman, P.S. Kandasamy, Panthera: design of a reconfigurable pavement sweeping robot, in: 2019 International Conference on Robotics and Automation (ICRA), 2019, pp. 7346–7352, https://doi.org/10.1109/ICRA.2019.8794268.
[176] V. Badrinarayanan, A. Kendall, R. Cipolla, SegNet: a deep convolutional encoder-decoder architecture for image segmentation, IEEE Trans. Pattern Anal. Mach. Intell. 39 (2017) 2481–2495, https://doi.org/10.1109/TPAMI.2016.2644615.
[177] L.C. Chen, G. Papandreou, I. Kokkinos, K. Murphy, A.L. Yuille, DeepLab: semantic image segmentation with deep convolutional nets, Atrous convolution, and fully connected CRFs, IEEE Trans. Pattern Anal. Mach. Intell. 40 (2018) 834–848, https://doi.org/10.1109/TPAMI.2017.2699184.
[178] M. Quigley, K. Conley, B. Gerkey, J. Faust, T. Foote, J. Leibs, R. Wheeler, A. Ng, ROS: an open-source robot operating system, in: ICRA Workshop on Open Source Software, 2009, p. 5. http://lars.mec.ua.pt/public/LAR%20Projects/BinPicking/2016_RodrigoSalgueiro/LIB/ROS/icraoss09-ROS.pdf.
[179] H.M. La, N. Gucunski, K. Seong-Hoon, J. Yi, T. Senlet, N. Luan, Autonomous robotic system for bridge deck data collection and analysis, in: 2014 IEEE/RSJ International Conference on Intelligent Robots and Systems, 2014, pp. 1950–1955, https://doi.org/10.1109/IROS.2014.6942821.
[180] M. Bloesch, S. Omari, M. Hutter, R. Siegwart, Robust visual inertial odometry using a direct EKF-based approach, in: 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2015, pp. 298–304, https://doi.org/10.1109/IROS.2015.7353389.
[181] The Deadliest Bridge Collapses in the US in the Last 50 Years. https://www.cnn.com/2018/03/15/us/bridge-collapse-history-trnd/index.html, 2018.
[182] R.S. Kirk, W. Mallett, Highway bridge conditions: issues for congress, in: 2018 TRB Annual Meeting, 2018. https://crsreports.congress.gov/product/pdf/R/R44459.
[183] H. Hao, W. Zhang, J. Li, H. Ma, Bridge Condition Assessment Under Moving Loads Using Multi-sensor Measurements and Vibration Phase Technology, Springer International Publishing, Cham, 2018, pp. 73–84, https://doi.org/10.1007/978-3-319-62274-3_7.
[184] J. Peng, S. Zhang, D. Peng, K. Liang, Application of machine learning method in bridge health monitoring, in: 2017 Second International Conference on Reliability Systems Engineering (ICRSE), 2017, pp. 1–7, https://doi.org/10.1109/ICRSE.2017.8030793.
[185] S. Gibb, H.M. La, T. Le, L. Nguyen, R. Schmid, H. Pham, Nondestructive evaluation sensor fusion with autonomous robotic system for civil infrastructure inspection, J. Field Robot. 35 (2018) 988–1004, https://doi.org/10.1002/rob.21791.
[186] A. Sirken, G. Knizhnik, J. McWilliams, S. Bergbreiter, Bridge risk investigation diagnostic grouped exploratory (BRIDGE) bot, in: 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2017, pp. 6526–6532, https://doi.org/10.1109/IROS.2017.8206562.
[187] N.H. Pham, H.M. La, Design and implementation of an autonomous robot for steel bridge inspection, in: 2016 54th Annual Allerton Conference on Communication, Control, and Computing (Allerton), 2016, pp. 556–562, https://doi.org/10.1109/ALLERTON.2016.7852280.
[188] H.M. La, R.S. Lim, B. Basily, N. Gucunski, J. Yi, A. Maher, F.A. Romero, H. Parvardeh, Autonomous robotic system for high-efficiency non-destructive bridge deck inspection and evaluation, in: 2013 IEEE International Conference on Automation Science and Engineering (CASE), 2013, pp. 1053–1058, https://doi.org/10.1109/CoASE.2013.6653886.
[189] T. Moore, D. Stouch, A Generalized Extended Kalman Filter Implementation for the Robot Operating System, Springer International Publishing, Cham, 2016, pp. 335–348, https://doi.org/10.1007/978-3-319-08338-4_25.
[190] P. Kaur, K.J. Dana, F.A. Romero, N. Gucunski, Automated GPR rebar analysis for robotic bridge deck evaluation, IEEE Trans. Cybernet. 46 (2016) 2265–2276, https://doi.org/10.1109/TCYB.2015.2474747.
[191] R. Xie, J. Yao, K. Liu, X. Lu, Y. Liu, M. Xia, Q. Zeng, Automatic multi-image stitching for concrete bridge inspection by combining point and line features, Autom. Constr. 90 (2018) 265–280, https://doi.org/10.1016/j.autcon.2018.02.021.
[192] B.W. Jiang, C.H. Kuo, K.J. Peng, K.C. Peng, S.H. Hsiung, C.M. Kuo, Thrust vectoring control for infrastructure inspection multirotor vehicle, in: 2019 IEEE 6th International Conference on Industrial Engineering and Applications (ICIEA), 2019, pp. 209–213, https://doi.org/10.1109/IEA.2019.8714892.
[193] N. Gucunski, B. Basily, J. Kim, J. Yi, T. Duong, K. Dinh, S.-H. Kee, A. Maher, RABIT: implementation, performance validation and integration with other robotic platforms for improved management of bridge decks, Int. J. Intellig. Robot. Appl. 1 (2017) 271–286, https://doi.org/10.1007/s41315-017-0027-5.
[194] N. Gucunski, S.-H. Kee, H. La, B. Basily, A. Maher, Delamination and concrete quality assessment of concrete bridge decks using a fully autonomous RABIT platform, Struct. Monit. Mainten. 2 (2015) 19–34, https://doi.org/10.12989/SMM.2015.2.1.019.
[195] R.S. Lim, H.M. La, W. Sheng, A robotic crack inspection and mapping system for bridge deck maintenance, IEEE Trans. Autom. Sci. Eng. 11 (2014) 367–378, https://doi.org/10.1109/TASE.2013.2294687.
[196] R. Raisutis, R. Kazys, L. Mazeika, V. Samaitis, E. Zukauskas, Propagation of ultrasonic guided waves in composite multi-wire ropes, Materials 9 (2016) 451, https://doi.org/10.3390/ma9060451.
[197] P.-C. Peng, C.-Y. Wang, Use of gamma rays in the inspection of steel wire ropes in suspension bridges, NDT & E Int. 75 (2015) 80–86, https://doi.org/10.1016/j.ndteint.2015.06.006.
[198] Z. Liu, Y. Cao, Y. Wang, W. Wang, Computer vision-based concrete crack detection using U-net fully convolutional networks, Autom. Constr. 104 (2019) 129–139, https://doi.org/10.1016/j.autcon.2019.04.005.
[199] Z. Zheng, N. Ding, Design and implementation of CCRobot-II: a palm-based cable climbing robot for cable-stayed bridge inspection, in: 2019 International Conference on Robotics and Automation (ICRA), 2019, pp. 9747–9753, https://doi.org/10.1109/ICRA.2019.8793562.
[200] N. Ding, Z. Zheng, J. Song, Z. Sun, T.L. Lam, H. Qian, CCRobot-III: a Split-type wire-driven cable climbing robot for cable-stayed bridge inspection, in: 2020 IEEE International Conference on Robotics and Automation (ICRA), 2020, pp. 9308–9314, https://doi.org/10.1109/ICRA40945.2020.9196772.
[201] F. Xu, S. Dai, Q. Jiang, X. Wang, Developing a climbing robot for repairing cables of cable-stayed bridges, Autom. Constr. 129 (2021), 103807, https://doi.org/10.1016/j.autcon.2021.103807.
[202] J.E. DeVault, Robotic system for underwater inspection of bridge piers, IEEE Instrum. Meas. Mag. 3 (2000) 32–37, https://doi.org/10.1109/5289.863909.
[203] C.A. Mueller, T. Fromm, H. Buelow, A. Birk, M. Garsch, N. Gebbeken, Robotic bridge inspection within strategic flood evacuation planning, in: OCEANS 2017 - Aberdeen, 2017, pp. 1–6, https://doi.org/10.1109/OCEANSE.2017.8084668.
[204] R.R. Murphy, E. Steimle, M. Hall, M. Lindemuth, D. Trejo, S. Hurlebaus, Z. Medina-Cetina, D. Slocum, Robot-assisted bridge inspection, J. Intell. Robot. Syst. 64 (2011) 77–95, https://doi.org/10.1007/s10846-010-9514-8.
[205] S. He, L. Kou, Y. Li, J. Xiang, Robust orientation-sensitive trajectory tracking of Underactuated autonomous underwater vehicles, IEEE Trans. Ind. Electron. 68 (2021) 8464–8473, https://doi.org/10.1109/TIE.2020.3013790.
[206] T. Ueda, H. Hirai, K. Fuchigami, R. Yuki, A. Jonghyun, S. Yasukawa, Y. Nishida, K. Ishii, T. Sonoda, K. Higashi, K. Tanaka, T. Ikeda, Inspection system for underwater structure of bridge pier, in: Proceedings of International Conference on Artificial Life and Robotics 24, 2019, pp. 521–524, https://doi.org/10.5954/ICAROB.2019.OS21-2.
[207] I. Yamamoto, A. Morinaga, M. Lawn, Agile Rov for underwater surveillance, J. Mar. Sci. Technol. 28 (2020), https://doi.org/10.6119/JMST.202010_28(5).0003.
[208] R. Bogue, What are the prospects for robots in the construction industry? Indus. Robot 45 (2018) 1–6, https://doi.org/10.1108/IR-11-2017-0194.
[209] E. Asadi, B. Li, I.M. Chen, Pictobot: a cooperative painting robot for interior finishing of industrial developments, IEEE Robot. Automat. Mag. 25 (2018) 82–94, https://doi.org/10.1109/MRA.2018.2816972.
[210] A. Więckowski, "JA-WA" - a wall construction system using unilateral material application with a mobile robot, Autom. Constr. 83 (2017) 19–28, https://doi.org/10.1016/j.autcon.2017.02.005.
[211] S. Goessens, C. Mueller, P. Latteur, Feasibility study for drone-based masonry construction of real-scale structures, Autom. Constr. 94 (2018) 458–480, https://doi.org/10.1016/j.autcon.2018.06.015.
[212] K.M. Lundeen, V.R. Kamat, C.C. Menassa, W. McGee, Autonomous motion planning and task execution in geometrically adaptive robotized construction work, Autom. Constr. 100 (2019) 24–45, https://doi.org/10.1016/j.autcon.2018.12.020.
[213] Y. Tan, S. Li, H. Liu, P. Chen, Z. Zhou, Automatic inspection data collection of building surface based on BIM and UAV, Autom. Constr. 131 (2021), 103881, https://doi.org/10.1016/j.autcon.2021.103881.
[214] K. Asadi, R. Jain, G. Qin, B. Sun, M. Noghabaei, J. Cole, K. Han, E. Lobaton, Vision-based obstacle removal system for autonomous ground vehicles using a robotic arm, in: The 2019 ASCE International Conference on Computing in Civil Engineering, 2019, https://doi.org/10.48550/arXiv.1901.08180.
[215] K. Asadi, A. Kalkunte Suresh, A. Ender, S. Gotad, S. Maniyar, S. Anand, M. Noghabaei, K. Han, E. Lobaton, T. Wu, An integrated UGV-UAV system for construction site data collection, Autom. Constr. 112 (2020) 103068, https://doi.org/10.1016/j.autcon.2019.103068.
[216] J.M. Davila Delgado, L. Oyedele, A. Ajayi, L. Akanbi, O. Akinade, M. Bilal, H. Owolabi, Robotics and automated systems in construction: understanding industry-specific challenges for adoption, J. Build. Eng. 26 (2019) 100868, https://doi.org/10.1016/j.jobe.2019.100868.
[217] K. Asadi, V.R. Haritsa, K. Han, J.-P. Ore, Automated object manipulation using vision-based Mobile robotic system for construction applications, J. Comput. Civ. Eng. 35 (2021), 04020058, https://doi.org/10.1061/(ASCE)CP.1943-5487.0000946.
[218] P. Kim, J. Chen, J. Kim, Y.K. Cho, SLAM-Driven Intelligent Autonomous Mobile Robot Navigation for Construction Applications, Springer International Publishing, Cham, 2018, pp. 254–269, https://doi.org/10.1007/978-3-319-91635-4_14.
[219] A. Gawel, H. Blum, J. Pankert, K. Krämer, L. Bartolomei, S. Ercan, F. Farshidian, M. Chli, F. Gramazio, R. Siegwart, M. Hutter, T. Sandy, A fully-integrated sensing and control system for high-accuracy mobile robotic building construction, in: 2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2019, pp. 2300–2307, https://doi.org/10.1109/IROS40897.2019.8967733.
[220] S. Karimi, R.G. Braga, I. Iordanova, D. St-Onge, Semantic optimal robot navigation using building information on construction sites, in: 38th International Symposium on Automation and Robotics in Construction (ISARC 2021), Waterloo, 2021, pp. 57–64, https://doi.org/10.48550/arXiv.2104.10296.
[221] C. Balaguer, R. Montero, J. Victores, S. Martinez, A. JardÓN Huete, Towards fully automated tunnel inspection: a survey and future trends, in: 31st International Symposium on Automation and Robotics in Construction and Mining(ISARC 2014), Sydney, Australia, 2014, https://doi.org/10.22260/ISARC2014/0005.

[222] E. Menendez, J.G. Victores, R. Montero, S. Martínez, C. Balaguer, Tunnel structural inspection and assessment using an autonomous robotic system, Autom. Constr. 87 (2018) 117–126, https://doi.org/10.1016/j.autcon.2017.12.001.
[223] J.G. Victores, S. Martínez, A. Jardón, C. Balaguer, Robot-aided tunnel inspection and maintenance system by vision and proximity sensor integration, Autom. Constr. 20 (2011) 629–636, https://doi.org/10.1016/j.autcon.2010.12.005.
[224] G. Yang, G. Wei, W. Guan, J. Dong, M. Han, Research on key technologies of cable tunnel inspection robot, in: 2019 Chinese Automation Congress (CAC), 2019, pp. 282–287, https://doi.org/10.1109/CAC48633.2019.8996713.
[225] S.C. Verma, R. Visgaard, A reactive control algorithm for 3D navigation of a non-holonomic robot in tunnel-like environments with static obstacles, in: 2020 Australian and New Zealand Control Conference (ANZCC), 2020, pp. 114–118, https://doi.org/10.1109/ANZCC50923.2020.9318399.
[226] X. Lin, D. Song, M. Qin, W. Zhang, X. He, B. Xie, An automatic tunnel shotcrete robot, in: 2019 Chinese Automation Congress (CAC), 2019, pp. 3858–3863, https://doi.org/10.1109/CAC48633.2019.8996350.
[227] H. Zhang, B. Su, H. Song, W. Xiong, Development and implement of an inspection robot for power substation, in: 2015 IEEE Intelligent Vehicles Symposium (IV), 2015, pp. 121–125, https://doi.org/10.1109/IVS.2015.7225673.
[228] L. Su, X. Yang, B. Cao, Y. Wang, X. Li, W. Lu, Development and application of substation intelligent inspection robot supporting deep learning accelerating, J. Phys. Conf. Ser. 1754 (2021), 012170, https://doi.org/10.1088/1742-6596/1754/1/012170.
[229] J.F. Allan, J. Beaudry, Robotic systems applied to power substations - a state-of-the-art survey, in: Proceedings of the 2014 3rd International Conference on Applied Robotics for the Power Industry, 2014, pp. 1–6, https://doi.org/10.1109/CARPI.2014.7030049.
[230] R. Guo, L. Han, Y. Sun, M. Wang, A mobile robot for inspection of substation equipments, in: 2010 1st International Conference on Applied Robotics for the Power Industry, 2010, pp. 1–5, https://doi.org/10.1109/CARPI.2010.5624455.
[231] Z. Shiling, Application of joint immune ant colony algorithm and fuzzy neural network to path planning and visual image processing of inspection robot in substation, in: 2020 3rd International Conference on Artificial Intelligence and Big Data (ICAIBD), 2020, pp. 142–148, https://doi.org/10.1109/ICAIBD49809.2020.9137437.
[232] K. Li, Z. Ye, J. Zhang, X. Chen, Control optimization method of substation inspection robot based on adaptive visual servo algorithm, J. Phys. Conf. Ser. 1676 (2020), 012195, https://doi.org/10.1088/1742-6596/1676/1/012195.
[233] X. Zhang, S. Liu, Z. Xiang, Optimal inspection path planning of substation robot in the complex substation environment, in: 2019 Chinese Automation Congress (CAC), 2019, pp. 5064–5068, https://doi.org/10.1109/CAC48633.2019.8996834.
[234] Z. Wang, R. Yu, T. Yang, J. Xu, Y. Meng, Robot navigation path planning in power plant based on improved wolf pack algorithm, in: ICISCAE 2021: 2021 4th International Conference on Information Systems and Computer Aided Education, New York, NY, USA, 2021, pp. 2824–2829, https://doi.org/10.1145/3482632.3487523.
[235] T. Siriborvornratanakul, An automatic road distress visual inspection system using an Onboard in-car camera, Adv. Multim. 2018 (2018), https://doi.org/10.1155/2018/2561953, 2561953.
[236] A. Sheta, S.A. Mokhtar, Autonomous robot system for pavement crack inspection based CNN model, J. Theor. Appl. Inf. Technol. 100 (2022). http://www.jatit.org/volumes/Vol100No16/19Vol100No16.pdf.
[237] Y. Geng, M. Yuan, H. Tang, Y. Wang, Z. Wei, B. Lin, W. Zhuang, Robot-based mobile sensing system for high-resolution indoor temperature monitoring, Autom. Constr. 142 (2022), 104477, https://doi.org/10.1016/j.autcon.2022.104477.
[238] N. Kayhani, H. Taghaddos, A. Mousaei, S. Behzadipour, U. Hermann, Heavy mobile crane lift path planning in congested modular industrial plants using a robotics approach, Autom. Constr. 122 (2021), 103508, https://doi.org/10.1016/j.autcon.2020.103508.
[239] M. Rahimi, H. Liu, M. Rahman, C. Ruiz-Cárcel, I. Durazo-Cardenas, A. Starr, A. Hall, R. Anderson, Localisation and navigation framework for autonomous railway robotic inspection and repair system, SSRN Electron. J. (2021), https://doi.org/10.2139/ssrn.3945953.
[240] W.-F. Li, H. Ding, K. Li, Q.-Z. Liu, X.-H. Jiang, Research on fault diagnosis method of tunnel inspection robot based on T−S fuzzy FTA, IOP Conf. Ser. 741 (2020), 012059, https://doi.org/10.1088/1757-899X/741/1/012059.
[241] M. Kouzehgar, Y. Krishnasamy Tamilselvam, M. Vega Heredia, M. Rajesh Elara, Self-reconfigurable façade-cleaning robot equipped with deep-learning-based crack detection based on convolutional neural networks, Autom. Constr. 108 (2019) 102959, https://doi.org/10.1016/j.autcon.2019.102959.
[242] S. Bodea, C. Zechmeister, N. Dambrosio, M. Dörstelmann, A. Menges, Robotic coreless filament winding for hyperboloid tubular composite components in construction, Autom. Constr. 126 (2021), 103649, https://doi.org/10.1016/j.autcon.2021.103649.
[243] X. Chen, H. Huang, Y. Liu, J. Li, M. Liu, Robot for automatic waste sorting on construction sites, Autom. Constr. 141 (2022), 104387, https://doi.org/10.1016/j.autcon.2022.104387.
[244] H. Chai, H.J. Wagner, Z. Guo, Y. Qi, A. Menges, P.F. Yuan, Computational design and on-site mobile robotic construction of an adaptive reinforcement beam network for cross-laminated timber slab panels, Autom. Constr. 142 (2022), 104536, https://doi.org/10.1016/j.autcon.2022.104536.
[245] S. Gusmao Brissi, O. Wong Chong, L. Debs, J. Zhang, A review on the interactions of robotic systems and lean principles in offsite construction, Eng. Constr. Archit. Manag. 29 (2022) 383–406, https://doi.org/10.1108/ECAM-10-2020-0809.
[246] D.A. Bennett, X. Feng, S.A. Velinsky, Robotic machine for highway crack sealing, Transp. Res. Rec. 1827 (2003) 18–26, https://doi.org/10.3141/1827-03.
[247] D. Bennett, S.A. Velinsky, Development of the Sealzall Machine: Upgrade to the TTLS (Pavement Crack Sealer), AHMCT research report, University of California, Davis. Advanced Highway Maintenance and Construction Technology Center, 2009, https://rosap.ntl.bts.gov/view/dot/25270.
[248] E.T. Mehran, K. Bilal, A. Mohamed, M. Nicole, L. Jason, J. Richard, R.C.D. F, C. D. N, F. Raul, M. Mark, R. Robert, P. Phil, Robotic and autonomous systems for road asset management: a position paper, in: Proceedings of the Institution of Civil Engineers - Smart Infrastructure and Construction 172, 2019, pp. 83–93, https://doi.org/10.1680/jsmic.19.00008.
[249] G. Zhu, Z. Fan, W. Chen, Y. You, S. Huang, W. Liang, R. Fu, J. Xin, J. Chen, F. Deng, Y. Hou, Design and implementation of a manipulator system for roadway crack sealing, in: 2019 IEEE 9th Annual International Conference on CYBER Technology in Automation, Control, and Intelligent Systems (CYBER), 2019, pp. 1327–1331, https://doi.org/10.1109/CYBER46603.2019.9066587.
[250] Y. Tsai, V. Kaul, A. Yezzi, Automating the crack map detection process for machine operated crack sealer, Autom. Constr. 31 (2013) 10–18, https://doi.org/10.1016/j.autcon.2012.11.033.
[251] M.E. Torbaghan, B. Kaddouh, M. Abdellatif, J.L. Nicole Metje, R. Jackson, C. Rogers, D. Chapman, R. Fuentes, M. Miodownik, R. Richardson, P. Purnell, Application of robotic and autonomous systems for road defect detection and repair - a position paper on future road asset management, in: Proceedings of the Institution of Civil Engineers - Smart Infrastructure and Construction, 2020, https://doi.org/10.1680/jsmic.19.00008.