Al-Khwarizmi Engineering Journal

Al-Khwarizmi Engineering Journal
ISSN (printed): 1818 – 1171, ISSN (online): 2312 – 0789
Vol. 21, No. 4, December, (2025), pp. 106- 124

Object Dimension and Location Determination in Gantry Robots and Conveyor Systems: A Review

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(Received 4 August 2024; Revised 11 January 2025; Accepted 10 April 2025; Published 1 December 2025)
https://doi.org/10.22153/kej.2025.04.012

Abstract

A gantry robot is one of the most common types of industrial robots with linear movement. This type of robot is also known as a Cartesian or linear robot. It is an automated industrial system that moves along linear paths, enabling it to create a 3D envelope of the space in which it operates. A robot of this type has a standardised configuration process because it can have several sets of axes, such as X, Y and Z. The gantry robot picks up products from several places, so it can search through various locations. Afterwards, it carefully deposits the products on a conveyor belt for the next stage of the procedure or final shipment. This integration enables continuous and automated material flow, increasing overall productivity and efficiency in manufacturing operations. Dimension measuring and object placement are critical tasks in robot and conveyor systems that depend substantially on the types of sensors. Progress in sensors and camera technologies has markedly enhanced precision, efficacy, productivity and adaptability. Sensors are commonly classified as range and vision sensors on the basis of their mode of measurement. This review article offers useful knowledge on gantry robots and conveyor systems and their historical background. It examines recent research that has reported on the advantages and disadvantages of gantry robots. Moreover, literature on object dimensioning and positioning via sensors and cameras in gantry robots is presented. This review elucidates the advantages and disadvantages of several sensing types, including cameras and conventional sensors. Comparisons of robotic systems in terms of accuracy, speed, cost, energy efficiency and other aspects are also performed. Many studies have been conducted on body detection via vision technology and sensors, but the use of laser sensors has received minimal attention and needs further focus in the future.

Keywords: *Gantry robot; Dimensions; Location; Sensors; Vision; Conveyor system*

1. Introduction

The use of robots in various industrial and commercial applications is increasing as robotic technologies develop [1]. These applications utilise robots to help humans perform tasks, and in some cases, they even replace humans [2]. Gantry robots can provide complete control of XYZ Cartesian space along a plane, allowing them to move at high speeds and perform pick-and-place operations with precision [3]. Gantry robots, equipped with gripping devices and conveyor systems, are one of the primary agents in the movement of parts, components and products [4]. Such pick-and-place and motion control operations mostly depend on

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these large-scale systems [5]. Determining human body dimensions is an indispensable task in numerous technological and industrial areas [6]. The success of these systems depends largely on sensor and camera technologies that help express factualness and effectiveness when imparting dimensions and design locations. Some sensors and vision technologies, where lasers, infrared and 3D cameras are involved, have been integrated to achieve the same goal through distance measuring and location pinpointing with high accuracy. Through these means, the required dimensions and locations can be monitored exactly, thus realising high process efficiency and outstanding performance in a wide range of industrial and scientific applications [7].

Some robotics equipment can determine the shapes and sizes of products for classification and sorting through vision [8]. Sensing and identifying the most crucial aspects in automated sorting systems that have emerged in this context and that demand thorough focus have been pointed out as crucial. Sensing involves not only the detection but also the classification of objects provided for sorting, which in turn requires advanced techniques in data handling and environment awareness generation [9]. Furthermore, grabbing, a stage that means attaining the target disunion with the highest degree of precision and effectiveness, should come first [10]. To make materials sufficiently capable, designers should produce mechanisms and devices that consist of intelligent algorithms and a strong processing unit so that the whole system will be reliable, and the sorting task will proceed with upgraded efficiency [11].

Cartesian or gantry robots should work along a rigorously marked route, and changes in object dimension and position detection should be minimal only. In a previous study, the researchers demonstrated a robotic system that could locate with high precision and subsequently pick up moving objects from a conveyor belt. The system employs the You Only Look Once (YOLO) algorithm for object identification, principal component analysis (PCA) for orientation prediction and template matching techniques for accelerating the motion of objects. An artificial neural network is in charge of the three-degrees-of freedom Cartesian manipulator that counterbalances the robot arm to ensure accurate understanding. In real dynamic scenes, the system achieves a success rate of 94.86% for vertically oriented objects and 91.43% for horizontally disposed ones, thereby setting the ground for its application in actual scenes [1]. Another landmark is the creation of a versatile, three-fingered robotic hand and a vision system to handle multiple objects in various scenarios. The gripper, equipped with visual serving, can perform real-time target tracking and uses a Raspberry Pi controller for movement. The design adjusts the grippers for different object shapes and attains 100% success in dynamic, non-visual environments. Such a solution is perfect for intelligent manufacturing because it facilitates calibration, reduces occlusion and increases precision [2].

In the industrial automation domain, a gantry robot has been constructed for pick-and-place operations with the help of a vision control system. Using Python and OpenCV, the robot decides whether to put the object in the blue or yellow drawer and then sends the respective control instructions to an Arduino Mega 2560 microcontroller. Devices like this are space and time savers, so they are in line with the principles of Industry 4.0 because they aim to streamline operational processes in tightly spaced environments [3]. A robotic work cell has also been developed to perform tasks, such as sole digitisation, glue application and grasping with an amount of variability that is typical of a footwear manufacturing environment. Equipped with RGBD cameras and laser scanners, the system determines the grabbing points for shoe soles of different shapes and sizes and achieves 97.5% success. The aforementioned robot methods resolve sophisticated manufacturing problems by minimising manual labour with high production efficiency [4]. Another approach is the use of two-finger grippers so that the system can grasp objects as they pass down conveyor belts and rotating platforms. This system provides real-time recognition and dynamic object tracking by applying the You Only Look at Coefficients model from object recognition and long short-term memory (LSTM) network and convolutional neural network (CNN) from trajectory prediction, which can be used for vehicles and pedestrians. All system components are integrated using the robot operating system (ROS), which is designed for handling objects in dynamic environments [5]. Research has also introduced a robotic gripper for industrial assembly tasks integrated with a vision system. The method automatically recognises the part's positions and determines the best points to grasp that part without previous training. Similarly, a robust, three-finger, adaptive gripper with ROS has been designed, and it is particularly suitable for high-mix, low-volume manufacturing scenarios where parts may be unstructured or randomly oriented [6]. For coal sorting, a delta-type parallel robot has been established for sorting coal and gangue on a conveyor belt. The system uses the Kemotion control system that combines vision and calibration methods to virtually configure the robot with the conveyor belt. This method increases not only recognition efficiency but also robot sorting accuracy, thereby decreasing manual labour [7]. Essentially, this study was the first to present a robotic manipulation system that uses event-based cameras to improve the robot's dexterity in tasks, such as grasping or drilling. The system is highly sensitive to motion and has very low latency and very high temporal resolution; thus, it can track fast-moving objects in a wide range of lighting conditions, and it does not compete but rather contrasts with conventional cameras. This ability provides the system more precision and more freedom than what is possible in traditional vision systems [8]. By integrating position- and image-based visual servoing, the authors developed a novel graphical framework that facilitates the design of mechatronic systems and makes the mechanical designs transition smoothly into electronics. Motion control, the main tool used by the virtual electronic auditors in this framework, is the means by which electronic data components are extracted; thus, designers can co-operate effectively. The system is compliant with IEC 61131-3, and particular libraries contribute not only to the clarity but also to the efficiency of mechatronic designs, especially when systems are complex [9]. Many other studies have also identified automating sorting as a key issue to be resolved by optimising pick-and-place operations. One study substantially altered throughput and system sorting accuracy by focusing on gripping efficiency and the implementation of dynamic scheduling algorithms that it can be regarded as a breakthrough. The system adjusts itself to various item flows through the use of simulations, so it can operate efficaciously at low costs [10].

Another study created a local automated order-picking system that addresses many orders simultaneously. The workstation is a blend of conveyor belts, robots and a carousel mechanism, leading to a reduction in processing time and an increase in productivity. Different types of picking policies were tested in the study, and a notable increase in throughput and decrease in system bottlenecks were achieved [11].

A gantry robot was built in another work to perform pick-and-place operations in material handling, and the robot was further upgraded with an obstacle detection capability. The robot is controlled by a programmable logic controller (PLC), and a vacuum cup is used to pick up objects gently. This automation leads to increased operational efficiency and reduced human labour and ensures safety in cases of obstacle interference during material transfer [12]. In another study, an automated storage and retrieval system (AS/RS) was created in the form of a gantry robotic cell with a conveyor belt and light sensors. Storage and retrieval operations are performed automatically by PLC. Through this integration, storage efficiency is improved, sorting and retrieval speeds increase, and human intervention is substantially decreased [13]. Meanwhile, another study designed a system for predictive maintenance of gantry cable-track systems to locate faults in critical industrial processes. The system relies on gyroscopes and accelerometer sensors to collect data for failure prediction and safety enhancement. The patterns from the diagnostic data of pumps were revealed, enabling the extraction of signatures and early warning methodologies, which were used for fault location through the two-group t-test in statistical analysis to determine the causes for cutting down maintenance costs and downtime [14].

In another work, a robotic arm for sorting, placing and counting was built. This system is coupled with a conveyor belt. When IR sensors detect an object on the conveyor, the system turns on an arm for precise material handling. Such a system reduces human intervention and raises the level of efficiency and accuracy in repetitive tasks; these capabilities are crucial for food processing and packaging and other industries [15]. Moreover, a gantry robot that can autonomously play checkers by using neural networks and computer vision has been introduced. The system employs reinforcement learning to make moves by combining the test board and pieces with a camera, and the camera feed is processed through OpenCV. Although the system faces substantial challenges in terms of lighting, it can play the game accurately and smoothly [16]. Meanwhile, a benchmarking study has reported that Q-Learning is more effective than State–Action–Reward–State–Action (SARSA) for robotic pick-and-place tasks in non-visual environments. Q-Learning, after being trained in several shapes, object dynamics and belt dynamics, can achieve more than 90% success, whereas SARSA has a lower success rate, especially for spherical objects and at high speeds [17]. The study examined the deployment of gantry robots and conveyor belt systems, with focus on the integration of vision and sensing technologies to elevate dimensional accuracy and operational efficiency. It conducted a detailed investigation of the advantages and disadvantages of gantry robots and highlighted the challenges in sensing, grasping and manipulation in these systems. Cartesian or gantry robots should move along a precisely defined path, with minimal changes in object dimensions and positional sensing. Sensors and camera vision can help determine body dimensions and position. This review discusses the gantry robot and conveyor system, including its working principle, advantages, disadvantages and types of sensors used and their working principle. The determination of body dimensions and position by range and vision sensors is discussed in detail.

2. Gantry Robots and Conveyor Belts

The gantry robot was first used in 1977 by R. A. Jarvis [18]. Gantry robots can make use of almost all their space and size, filling up to 96% of their cubic work envelope [3]. A Cartesian robot has three axes for operation. X, Y and Z typically denote coordinates in three dimensions (Figure 1). The arrangement of each axis is perpendicular, enabling three degrees of mobility [19]. Unlike robots with arm configurations, gantries can easily expand to large dimensions in all three axes. Gantry robots are particularly suitable for situations with few additional orientation constraints or where the robot can arrange the pieces in advance before picking them up [3]. Cartesian and gantry robots have a rectangular or cubic work envelope, unlike articulated robots, which, similar to the joints in a human arm, have defined boundaries for each movement and a predefined range of motion. Consequently, the degree of movement is represented by wide, sweeping arcs, which are the main depiction factors. These arcs illustrate positive and negative degrees of movement as they rotate around the centre of the base and the bearing of each axis. Notably, these non-standard work areas often entail changes to the workspace, instead of the robot modifying the environment [20].

Cartesian/gantry robots have an extremely high level of accuracy and repeat ability as a result of their rigid yet lightweight structure. Gantry robots are easy to program and deploy when assessing new automation because of their straightforward structures. Most gantry robots are customisable. Equipped with a wide range of motor and gearbox options as well as various components and materials, these robots are ready to address the difficulties posed by damp, dangerous, unclean environments [21]. The Cartesian coordinate robot's simplistic form and uncomplicated operation make it highly favoured in the industrial industry. By allowing for easy replacement of individual axes, the system minimises downtime and keeps maintenance costs low. Furthermore, the entire system can be dismantled into its constituent elements for use in other single-axis applications. Moreover, Cartesian coordinate robot systems are more cost effective than intricate robots [22].

The use of the conveyor belt began in 1909 [23]. In May 2024, Lim Jun designed and developed a conveyor belt system. This system, which moves materials and items from one location to another with high accuracy and speed, plays a crucial role in manufacturing and production facilities. The conveyor belt is essential for continuous, stable operation because it ensures that the production line and storage distribution centre function smoothly. The conveyor belt structure consists of mechanical and electronic components that work together to optimise usage while allowing production to be achieved without errors or downtime [24]. An automated conveyor belt relies on advanced electronic systems, which are composed of microcontrollers and sensors that interact with the environment as needed. Polyvinyl chloride is used to make this conveyor belt, which is known to be durable and highly resistant to heavy loads and wear. Given that it allows for easy and secure transportation of products, this system is ideal for various industries, especially in the food industry where the conveyor belt is made from either thermoplastic elastomers or stainless steel, adding to its resistance to corrosion [25].

Wear- and corrosion-resistant metal rollers are the belt's supporting elements, and they guide it during operation with damping vibration. The conveyor is powered by different kinds of electric motors, such as AC motors that deliver continuous power for heavy-duty applications, DC motors that provide variable speed for precise speed control and servo motors that automatically adjust conditions with dynamic response to high-level control in complex operations. Notably, many other high-end technologies (e.g. PLC control for the conveyor, where PLC manages the belt speed and direction depending on the data received from sensors and cameras) are available [26]. Sensors provide exact information about product weights and locations, and cameras, being a part of the machine vision system, detect quality issues, such as damage or misclassification. These combined systems make up an ideal approach to minimise waste and maximise production efficiency. They have robust engineering and integrated technology to implement quality and safety solutions for products during transit [27].

The carriage is aligned with the gripper at the specified corner on the basis of the PLC signal, and the conveyor belt stays immobile, awaiting the item. The gripper seizes the object and deposits it on the conveyor belt at the specified home position. A signal is then sent from PLC to commence the conveyor's operation for the item specified for retrieval [28]. Shubha and Rudresh concentrated on a project involving a colour sensor-based object-sorting robot, with the primary purpose of developing an automated material handling system. The item on the conveyor belt is retrieved when the microcontroller instructs the robotic arm by synchronising its movement. All items are organised by positioning them in their designated locations after being retrieved from the conveyor. Accuracy and repeatability in tasks are attained when human labour is performed by robots [29].

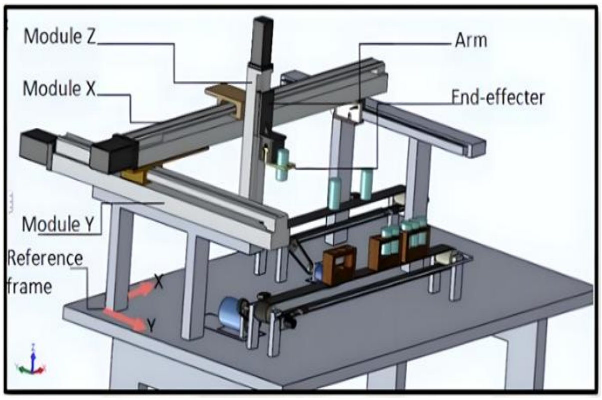

Fig. 1. Gantry robot [3]

3. Advantages and Disadvantages of Gantry Robots

3.1. Gantry Robot Advantages [30, 31, 3]

1. The robot is capable of extremely fast and accurate item repositioning, which is an absolute necessity in such industries as medical device assembly and semiconductor manufacturing to guarantee excellent results [30].
2. Gantry robot systems can be used in logistics and manufacturing. They can carry different weights and sizes of items, making them perfect for 3D printing, milling and pick-and-place systems [31].
3. Cartesian robots always have the same shape even when the tool is in a different location. Gantry systems are modular, so they can be easily scaled up or down for large or small objects depending on the project needs [31].
4. Compared with other robotic systems, such as articulated arms, gantry robots can take advantage of their vertical and horizontal dimensions much more effectively, hence reducing the distance to the components, decreasing the amount of guide way material and ultimately conserving floor space [3].

3.2. Gantry Robot Disadvantages [32, 33]

1. Gantry robots need a large area for installation because of their sizable frame and long travel range [32].
2. The installation of gantry robots is usually a complicated and lengthy procedure, and it may require specialised knowledge and equipment [33].
3. The cost of a gantry robotic system is a considerable one at the outset; this cost is inclusive of the expenses of the robot, the installation and any necessary changes to the facility [33].
4. Gantry robots might not be suitable for tasks that are complicated and require multi-directional movements or operations in a confined space [33].
5. Given their large size and lengthy axes, gantry robots can have vibration and resonance problems, especially when operating at high speeds [33].

4. Determination of Body Dimensions and Position by Range Sensors

A gantry robot has sensors to determine the measurements of the body and the subject. The precision and effectiveness of a sensor in locating and measuring the body depend on the degree of its interaction with various production and processing programs in the robot. Combining sensor aids can improve the accuracy of the position and speed of determining the objects [34]. In a previous work, a method involving merged visual and proximity sensing of a reticular structure was established to capture objects [12]. The technique ensures that both sensors provide overlapping cover for the region in question. The sequence of motion employs a control base to predict the trajectory of the object as it goes to the desired position, correct approach errors and grab the object firmly [35]. Another study integrated vision and proximity sensors into the robot to enhance its capability. The vision sensor helps locate the route by checking a large area [24], and the proximity sensor, which is in the hand's mesh structure, eliminates the errors of the approach; only then can the hand grasp the object. The integration instigates the hand's skill of environmental perception [36]. Various control loops can be used for coordinating the gantry robot's actions with those of the conveyor system [16] operating at a regular speed. As a result, the system can calculate an object's position with high accuracy and retrieve it [13]. Moreover, the body can be located and measured in numerous ways [37] a result of rapid technological developments and brilliant inventions [38], especially with regard to storage and retrieval operations. A sensor is an input device, and it is part of a cohesive system. The sensor of this system sends a signal to the main control unit. The sensor receives an analogue signal (e.g. temperature, humidity, colours and light) that is continuous and obtained from the surrounding environment [39].

Advanced industrial robotic systems have upgraded the extent to which we are able to determine the dimensions and positions of objects via integrated advanced sensors, algorithms and dynamic control systems. The sensor changes the input into a digital electrical signal that can be understood by the main controller, which issues suitable system commands. For example, Peng Wang et al. invented a mechanism that locates and measures the positions of objects on conveyor belts in motion by using optical sensors. The information was translated into real-world units through mathematical modelling, and a particle swarm optimisation (PSO)-based control system was used to adjust robot trajectories; minimal position and speed errors were obtained, showing the system's capability for dynamic target operations [40]. Similarly, Hanson et al. presented the PROSPECT system that merges spatial and spectral data by using Azure Kinect time-of-flight cameras and visible and near-infrared (VNIR) spectrometers, resulting in precise material quality evaluation and non-destructive defect detection and paving the way for new industrial applications in material analysis [41]. Kiyokawa et al. employed RGB-D cameras, NIR spectral sensors and motion planning algorithms, such as MoveIt, to direct robotic arms in the industrial waste mixture sorting process; this approach reduces manual labour, improves sorting accuracy and increases material adaptability capabilities [42].

Soetedjo et al. enhanced sorting functionalities by creating a system that employs ZX distance and gesture sensors and TCS3200 colour sensors to study the object location, dimensions and colour on conveyor belts, thus confirming the sorting accuracy in assembly lines and material verification [43]. Ljutjuk et al. developed an AS/RS powered by RFID sensors for accurate item tracking. The system, powered by FlexSim software, employs mechanical agents, such as forks and suction cups, to enhance operational efficiency, reduce errors and meet high-performance standards [44]. Ku et al. were the first to build a Cartesian robotic system for sorting construction and demolition waste. They used laser sensors to create 3D images of objects and advanced algorithms (e.g. Newton–Raphson) to determine the ideal grasping points. With an output of 2,000 items per hour and a success rate exceeding 90%, this system demonstrates a high level of efficiency in managing various materials [45]. Bargiotas et al. created a gantry robotic system for AS/RS that employs laser sensors for the identification of objects and PLCs for accurate guidance of the robotic arm. This system optimises storage and retrieval operations, decreases costs and increases accuracy [13].

Carlsson et al. created a robotic claw mechanism that leverages infrared and ultrasonic sensors to follow and grab fast-moving objects in real time. The Arduino UNO-controlled system demonstrated the success of the infrared sensor in dealing with a fast-moving object, therefore providing a few ideas for potential enhancements of sensor integration and algorithms [46]. Meanwhile, Akrawi developed a masonry robot system equipped with ultrasonic and laser sensors for precise alignment of building blocks in a construction site. The system, which is pilot-guided by a rule-based expert system, allows accuracy even in unpredictable environments; thus, it reduces mistakes and increases productivity [47]. These studies have revealed substantial advancements achieved in the integration of sophisticated sensors, optimisation algorithms and dynamic control systems for the improvement of the determination of the dimensions and positions of objects in applications in different industries. Internal and external sensors are frequently utilised sensor types. Robots employ external sensors to gather data, including the specific location where the robot comes into contact with the product it is manipulating, from the surrounding environment. Distance sensors are commonly classified in accordance with their mode of measurement [48]. The following section presents commonly acknowledged sensor categories.

4.1. Ultrasonic Sensors

Ultrasonic sensors were frequently utilised in the past, but advancements and cost reductions in alternative sensing technologies have reduced their frequency of use. An ultrasonic sensor is a device that can measure distance and object speed without making physical contact. It operates by utilising sound waves at a frequency higher than the range of human hearing (Figure 2) [49].

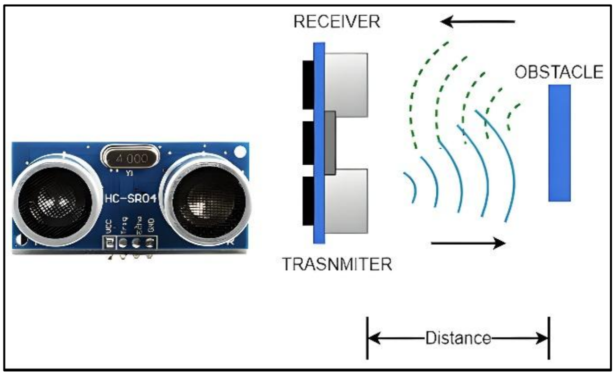

Fig. 2. Working principle of ultrasonic sensors [49]

The following drawbacks diminish the competitiveness of ultrasonic sensors.

- Sound experiences deflection when it strikes inclined surfaces, resulting in measurement mistakes.
- The proximity of the sensors causes interference.
- The precision of the measurements depends on the amount of intricacy.
- Sample collection is relatively slow.

The main advantages of this sensor are its low price and ability to withstand fog and dust. The HC-SR04 ultrasonic ranging module features a non-contact measurement capability and can measure distances from 2 cm to 400 cm. It has a ranging accuracy of up to 3 mm. The modules consist of ultrasonic transmitters, receivers and control circuits. The fundamental work premise is as follows:

1. An IO trigger is used to generate a high-level signal with a duration of at least 10 μs.

2. The module independently emits eight 40 kHz pulses and identifies the existence of a corresponding pulse signal.

If the signal returns at a high level, the duration of the high-output IO represents the time it takes for the ultrasonic signal to be sent and returned. The formula to calculate the distance is as follows:

$$D = (t \times v) / 2, \quad (1)$$

where D is distance (mm), t is time (s) and v is the velocity of sound (340 m/s).

4.2. Infrared Sensors (E18-D80NK)

An infrared sensor typically finds the distance to an item by sending out infrared light signals and determining the reflection angle by triangulation. When an infrared light-emitting diode (LED) sends a beam of light to an object, the light is reflected in various directions. The proximity sensor, which is located near the infrared emitter, sees a light wave that has been reflected. The proximity sensor determines the distance to the object by using the angle at which the signal was sent [50]. The working process of an infrared sensor is explained in Figure 3 [51].

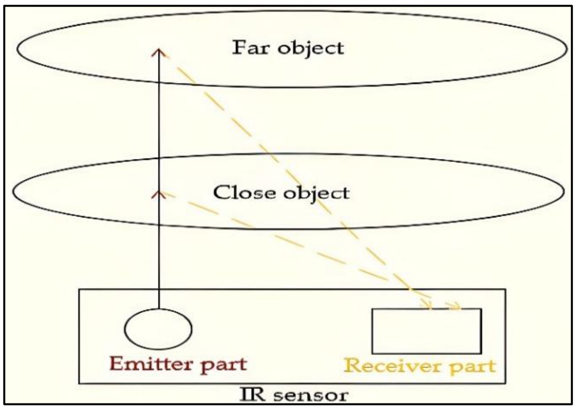

Fig. 3. Triangulation procedure of the infrared sensor [51].

Infrared LEDs emit a very narrow beam of light to a particular area of a nearby object. The object reflects the optical signal; thus, the signal reaches the proximity sensor at an angle. The proximity sensor uses this information to perform a mathematical calculation of the distance. The E18-D80NK digital infrared sensor is equipped with a distance detection feature. A potentiometer with a range of 3–80 cm can be used to determine the measurement. An infrared transmitter emits infrared light in each sensor, and an infrared receiver detects the reflected infrared light from the object. This sensing enables the sensor to confirm if the object is within a specified range. The diagram of the implemented infrared sensor is E18-d80nk. Interference has an extremely low chance of disturbing visible light. Therefore, the external influences have a very minimal effect on the error margin [52].

4.3. Light Detection and Ranging Sensors

Light detection and ranging (LIDAR) sensors use ultrasonic and infrared sensors as their basic tools. The light component of LIDAR sends a laser beam towards the target to determine the distance. Then, the target area gives off a light signal that bounces off and is picked up by the LIDAR device. The amount of time the laser signal took to travel is multiplied by the speed of light in the air to locate the place of the object, as shown in Figure 4. This method allows tiny objects to be pinpointed at the most accurate level of precision that is of the highest order (e.g. 0.005% of the final range). However, these sensors are costly in a few instances, and some of them may be dangerous to human eyes [53, 54].

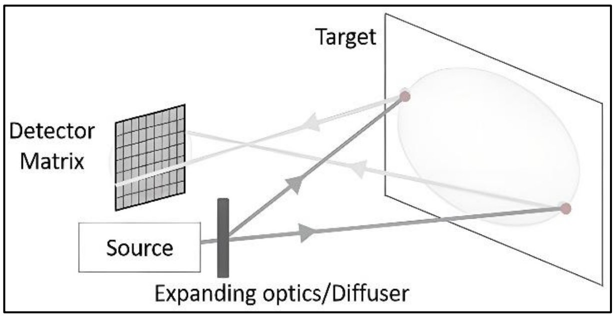

Fig. 4. Measurement principle of LIDAR sensors [54].

4.4. Laser Sensors

Laser sensors are mainly used to measure physical characteristics, such as distance, velocity and vibration. Typical laser instruments include laser range finders, laser displacement sensors, laser scanners and laser trackers. The core of laser range measurement involves three basic concepts: time of flight (TOF), triangulation and optical interference. TOF refers to the time interval from when the laser is sent to when the reflected light is received [50]. The laser range finder is a tool that measures long distances [51]. The TOF method is predominantly employed when long distances are to be measured. These instruments are specially designed to sense their targets. The setup utilises a transmitter diode to generate short bursts of infrared light that hit the surface. The object reflects light, which is then detected by a receiver diode through transmission and reception. The brightness levels are compared, and the sensor's distance from the object is calculated [52].

Measurement accuracy in TOF is limited by the precision of the measurement, which is in turn restricted by the high speed of light. The laser distance sensor uses a very narrow beam of light to determine the exact distance to a certain item. Recognition and detection of 3D objects, regardless of their nature, colour and brightness, are also performed. The triangulation method applies the concepts of homothetic triangles and trigonometric functions to conduct measurement calculations and locate elements relative to each other. The laser displacement sensor implements this method to achieve measurements at short distances [55]. Optical interference is the result of the overlap of two light beams of different wavelengths, leading to the formation of an interference pattern. The phase makes the stripes bright and shadowed. Displacement measurement by the laser tracker is one of the applications of this technology. The distance to the target is determined by using a sensor equipped with a reflector. Laser sensors can perform non-contact distance measurements (Figure 5), and they are very fast and accurate. However, variations in temperature and atmospheric pressure could influence the wavelength of a laser. Changes in atmospheric humidity and moisture content may require modifications to be made [53].

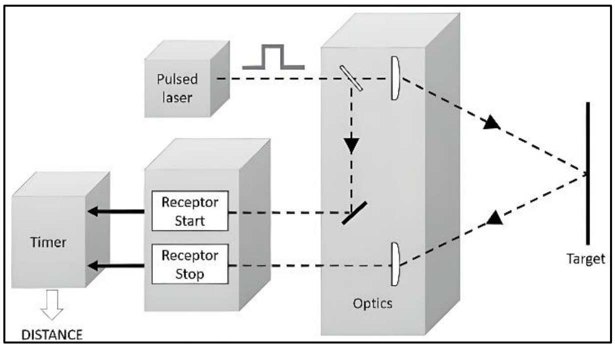

Fig. 5. Time-of-flight measurement principle [54].

5. Determination of Body Dimensions and Position by Vision Sensors

A purely event-based visual service method can be employed to solve automated processing tasks; for example, an event camera can be used in eye–hand configuration, and multiple perception algorithms with vision-based robotic controllers can be adopted to manage the robot's movement during processing tasks [56]. The vision system undertakes the acquisition and analysis of field images to detect objects then sends the coordinates of these objects to the gantry robot. Industrial processes have placed increasing demands on automation, resulting in substantial advances in robotic vision (e.g. object identification, tracking and manipulation). For example, a stationary camera system using HIKVISION industrial cameras is employed to view a conveyor belt, and a mobile camera is mounted on the arm of a robot helps pick items and assemble them. Using Halcon software, the system performs image processing tasks, such as calibration, edge detection and template matching, reporting the object's size, position and orientation even when data are incomplete. This method had a success rate of over 98% and substantially reduces production cost and manual labour [57].

In other instances, a dual-robot arm is used with an RGB camera to classify and sort objects by their shape and size. The optics and technologies system adopts image processing techniques, such as greyscale conversion, noise filtering and contour extraction, to detect objects and compute their centroid. The calculated 3D coordinates can be used by the robot to efficiently handle and classify items on production lines [58]. For complex object grasping, a neural network method, such as ASP U-Net, takes in RGB images, which are converted into greyscale maps to identify possible succour points. Then, the dimensions of an object and its position distance are calculated from one point to another point. This approach is memory-light and usable on low-cost devices, such as NVIDIA Jetson Nano [59]. For example, in waste-sorting applications, a robot autonomously learns how to efficiently pick items. A heightmap of the conveyor belt to find object positions is created using a 3D camera. This process involves an initial geometric algorithm that identifies candidate gripping points, followed by refinement through a machine learning model that learns which of the points succeed through gripping feedback. The system can clear the conveyor belt by scanning and picking most of the objects over time. The performance of this iteration is improved, allowing the system to learn and adapt efficiently [60]. Moreover, a trajectory planning method is used to coordinate robot activities with dynamic targets to follow and understand fast-moving objects.

The robot used in industrial vision systems and real-time sensors can calculate the motion from the object and estimate an optimal trajectory. A seven-stage planning model considers limitations (i.e. acceleration and speed), and PSO minimises the execution time and achieves high tracking accuracy [40]. Meanwhile, an approach in the context of robotic welding employs a three-degrees-of-freedom manipulator paired with a camera for process detection and tracking of seams. Algorithms, such as canny edge detection and top-hat transform, are used to process images, helping identify the welding line to show the path for the robot to follow. An adaptive neuro-fuzzy inference system is incorporated for precise kinematics, which enhances welding performance and reduces errors [61]. A lightweight CNN in a YOLOv3-tiny-based model has also been used in object detection for real-time object segmentation in manufacturing. A pixel-level feature analysis for detecting object boundaries is achieved using the intensity-difference search (IDS) algorithm for segmentation improvement. This system is utilised to calculate the dimensions and orientation of an object correctly, and grasping is performed accordingly; it is suitable for smart factories [62].

The latest technology that is being used in thermal forming for ship fabrication is a laser scanning system that detects the boundaries and surfaces of curved plates and thus generates precise data for heating instructions. By using this information, the system controls a high-frequency induction heater mounted on a robotic arm to conduct the procedure, resulting in an efficient, automated process [63]. Then, an object classification system on moving conveyor belts identifies and processes images to sort objects. The images are processed, and unwanted areas of images are discarded. Running algorithms, such as canny edge detection and PCA-SIFT, are employed to distinguish objects in images on the basis of colour, contour, or shape. The use of this system in dynamic industrial settings satisfies real-time performance constraints by enabling fast sorting and picking [64]. Different types of cameras are adopted in different situations to determine the physical dimensions and position of the body in the case of robots. Conventional RGB cameras take detailed images, which can be further processed to extract depth and dimensions with the help of a machine learning algorithm (Figure 6) [65].

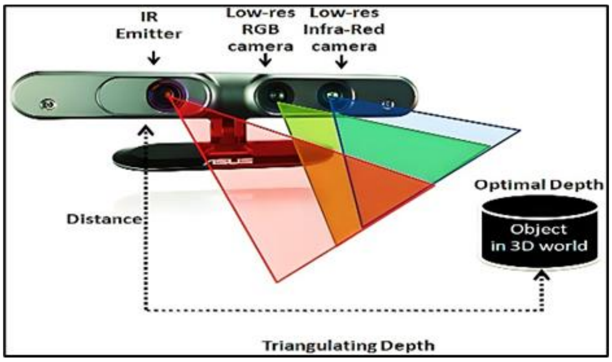

Fig. 6. Diagram of object capture by an RGB-D camera [65].

As shown in Figure 7, stereo vision cameras typically comprise two or more cameras situated at different angles and are frequently employed to obtain depth information via disparity analysis. TOF cameras are mainly preferred because of their effectiveness. They send out modulated light signals and determine the time needed for the light to return, thereby generating accurate 3D maps of the scene. Structured light scanners project patterns on objects and analyse the deformation of these patterns to reconstruct 3D shapes accurately [66].

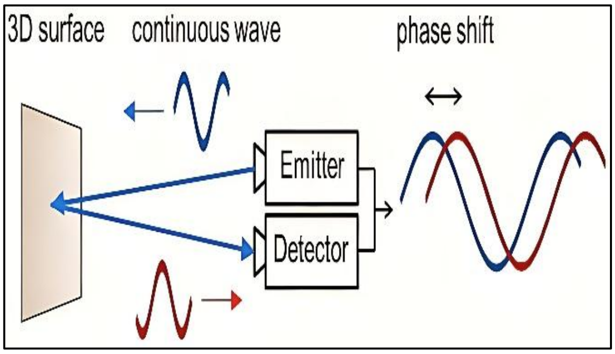

Fig. 7. Time-of-flight camera principle [66].

Furthermore, RGB-D cameras that merge RGB imaging with depth sensors, such as Microsoft's Kinect or Intel's Real Sense, offer total colour and depth data that are very helpful for accurate positioning and measurement. LiDAR devices, which are known for aiding in navigation and detecting obstacles, can also be used to produce detailed 3D models of a robot's surroundings. These camera technologies allow robots to obtain exact measurements and positioning, thus increasing their working capabilities and ability to adapt to the ever-changing environment. To solve the aforementioned problem, researchers have developed a vision-based control system that makes the system dynamic in nature. A USB camera is used to take images, and these images are handled by open-source software, such as OpenCV, in computer vision. The microcontroller converts the particular object in the photo by accurately recognising the colours and features [27].

5.1. Advantages and Limitations of RGB-D Cameras [65, 66, 67]

5.1.1. Advantages of RGB-D Cameras [65, 66, 67]

The advantages of RGB-D cameras are as follows:
1. Adequate energy performance [65],
2. High frame rate and long battery life [65],
3. Passive high resolution [66],
4. Generates a 3D representation of an object or scene with coloured data points [66],
5. Classification of accuracy among objects that are comparable [67].

5.1.2. Limitations of RGB-D Cameras [65, 66, 67]

The limitations of RGB-D cameras are as follows:
1. Robust non-textured regions [65];
2. Low-precision distance measurement, thermal stability, and repeatability [66];
3. Lack of features in scenes [67];
4. No correspondence in different views of the camera [65].

A summary of the methods used for object identification, dimension measurement and position determination via range and vision sensors in robotic conveyor belt systems is given in Table 1.

Table 1.
Summary of the Methods Used for Object Identification, Dimension Measurement and Position Determination in Robotic Systems

	The object is identified	Dimensions are measured	The position is determined
Peng Wang et al. [40]	Optical sensors identify objects located on moving conveyor belts. Mathematic	Mathematic modelling converts sensor data into real-world measurements.	Based on sensor data, this approach uses particle swarm optimization to optimize robot trajectories.
Nathaniel Hanson et al. [41]	Spatial and spectral data are collected via Azure Kinect Time-of-Flight cameras and VNIR spectrometers.	Spectral data provides material analysis, contributing to dimension estimation.	The 4D model combines spatial and spectral information for position characterization.
Takuya Kiyokawa [42]	RGB-D cameras, NIR spectral sensors, and motion planning algorithms index objects.	Dimensions are estimated based on the assessment of camera data and sensor readings.	The robotic arm is guided by the MoveIt algorithm, which takes the position and dimensions of the object into account.
Aryuanto Soetedjo [43]	ZX Distance and Gesture Sensors, TCS3200 Color Sensors, filtering objects on conveyor belts.	ZX and color sensors measure the geometric location, dimensions, and color of objects.	The position comes from some processing of sensor data by an Arduino Mega2560 controller.

Conrad Ljutjuk [44]	RFID sensors monitor the location of items in cases like ASRS (Automated Storage and Retrieval System).	Physical instruments (e.g., pressure gauges and vacuum devices) measure dimensions of objects.	RFID incorporated into FlexSim inform object positions.
Yue-Dong Ku [45]	Laser sensors create 3D images of objects for sorting and identification.	Object dimensions are computed using 3D pictures produced by laser sensors.	Robust algorithms (e.g., Newton-Raphson) improve the focal point and position.
Ata A. [13]	This uses laser sensors to classify objects by adding laser beam interruption.	Object classification via laser sensors helps measure the dimensions of the objects.	Robotic with position-based PLC-based control can store and retrieve items.
Matthias Carlsson [46]	Infra-red and ultrasonic sensors detect movement that can be identified.	Infrared and ultrasonic sensors detect the shape and distance of fast-moving objects.	The sensors perform position tracking in real-time, while gripping is done using algorithms.
Shereen Ghanim Akrawi [47]	Block Identification: Ultrasonic / Laser sensors for construction environments	The sensors take real-time measurements of the blocks' dimensions.	It uses rule-based expert systems to process sensor information and define the treatment process precisely.
Cong, V. D.et al. [57]	Uses HIKVISION industrial cameras for visual identification	Uses Halcon software, minimum rectangle fitting for dimensions	Uses image processing, template matching, and edge detection for location determination
Dolezel, P.et al. [58]	Image processing (grayscale, noise filtering, contour extraction, classification based on area, perimeter, and compactness)	rea (using image moments), perimeter, and compactness c=p2Ac = \frac{p^2}{A} are calculated to identify the shape and size.	Centroid (Cx, Cy)(C_x, C_y) is calculated using image moments. It is converted to 3D coordinates relative to the camera's frame.
Stogl, D.et al. [59]	ASP U-Net detects grasping points and highlights them with geometric gradient shapes.	The distance between grasping points is used to estimate the size of the object.	2D pixel coordinates (X, Y) of grasping points are passed to the robot arm. No 3D information is used.
Peters A et al. [60]	- Uses a 3D camera to create a heightmap of the conveyor. - Geometric algorithms propose initial gripping points. - Machine learning refines the best picking point.	Extracts object dimensions from the heightmap data provided by the 3D camera.	Computes the object's location relative to the conveyor using the 3D heightmap and calibrated coordinates of the robot's gripper.
Wang, P et al. [40]	Employs industrial vision or sensors to locate moving objects. - Tracks real-time position using conveyor speed and direction data.	Computes object dimensions from optical or sensing inputs integrated into the mathematical trajectory planning model.	Determines the location based on real-time tracking of object motion using vision or sensors integrated with trajectory planning.

Al-Karkhi, N. K.et al. [61]	Utilizes a camera to capture images of the workpiece. - Image processing algorithms detect edges and weld seams (e.g., Canny Edge Detection, Top-Hat Transform).	Measures dimensions by converting image coordinates to real-world dimensions using intrinsic and extrinsic camera calibration.	Uses edge detection and weld seam identification in image processing to locate the target line relative to the camera's calibrated plane.
Cho, J.et al. [62]	Uses YOLOv3-tiny for real-time detection	The IDS algorithm extracts precise object boundaries	Geometric analysis calculates position, orientation, and grasping points
Park, J.et al. [63]	Pre-scanning with multi-LVS detects plate location in the work area	Detailed measurement using Local-LVS, approximations via NURBS curves	Position and curvature derived from 3D surface approximations
Tran, H.N.et al. [64]	Analysis of images captured by a camera, using thresholds for color detection and edge contour analysis	Simplifies object shapes into polygons based on edges	Calculates the center of mass and angle from polygon vertices

6. System Performance Criteria

Modern-age robotic systems are crucial for enhancing the efficiency and performance correctness of different industrial tasks. However, these systems entail trade-offs in terms of reliability, throughput, price and power draw, so the choice of which is ideal for a given application tends to be highly application specific [68]. A comparison of several robotic systems in terms of important parameters, such as accuracy, speed, cost and energy efficiency, is provided as follows:

1- With regard to systems used for precision applications, such as micro-assembly, Cheng-Yen Chen [20] studied ways to improve positioning accuracy in bridge systems. Laser Doppler displacement measurement techniques were used to identify spatial errors, and compensation logic on the basis of a B-spline command generator was developed. The outcome was 50% more accurate than the standard outcome of ±3 µm. Given the use of advanced technologies, this approach has a high initial cost but offers high energy efficiency with permanent magnet motors.

2- Sharath et al. [3] highlighted that the Arduino-based gantry robot achieves an accuracy of only 85%–90%; it is limited by the precision of the stepper motors and the computational capacity of the Arduino Mega 2560 microcontroller. Its velocity is moderate, which is suitable for minor tasks. This system is economical because of the use of readily accessible components and simple hardware. Energy consumption is negligible because of the use of lightweight materials and low-power components.

3- Vall et al. [19] worked on a bridge robot design that uses linear motors and inductive sensors, resulting in high precision and safety. The design is responsive to the requirements of tasks with a high applied speed, with its maximum speed of 6,000 mm/s. The system is expensive to install, but because of its energy conservation and low maintenance, it could provide cost savings after some time.

4- Thatere et al. [12] presented a controlled scenario where human-like accuracy is obtained through proximity sensors; however, the exact numbers were not given. The presented system has slow motion and uses 200 RPM DC motors, which are typically utilised in elementary pick-and-place operations. By employing common components and consuming the least energy possible (the system depends on low-power motors and pneumatic systems), the technology is economically efficient.

5- Freeman et al. [26] demonstrated that by using iterative learning control (ILC) to reduce errors in task repetition, the system can achieve an accuracy of over 99%. The speed is extremely high due to the optimisation of the motion trajectories. However, the costs are high because of the difficulties in implementing ILC, but the energy consumption is efficient because unnecessary movements were minimised.

6- Kujala et al. [27] presented a system that is only 87.5% accurate at first; then it improves through machine learning. This unit performs very fast work, changing or selecting in under 1.8 seconds. Although it is flexible, its costs and energy consumption are high because it depends on advanced computer resources and continuous learning processes.

7- Shang and Wang [7] explored a mechanism that leads to an increase of 72.3% in calibration accuracy. The system works at an average speed because it can process seven images in a second. The costs are low because minimal maintenance is required as a result of accurate calibration, and the power consumption is moderate because the system is optimised through the elimination of unnecessary movements.

8- Wang et al. [40] reported that the method in question achieves a phenomenal 99.8% accuracy in the localisation and sorting of objects. The speed is moderate, and the variation is 7.4 mm/s. The expenditure is also minimal because of reduced wear and tear resulting from improved trajectory planning. The energy consumption is made efficient by the removal of unnecessary movements.

The ILC gantry robot is an example of a device that can be used in situations that require a combination of high precision and high speed. It is known for its accuracy of more than 99% and quick performance, so it is suitable for clean rooms that require continuous high throughput and precision even though it has a drawback of high cost and high energy consumption. For economic efficiency and reasonable precision, the Arduino-based gantry robot offers an economical solution with an accuracy of 85%–90%, making it suitable for small-scale operations, educational applications, or prototypes where budget limitations are critical. The ILC gantry robot is the ideal choice for scenarios requiring precision and speed, especially in high-volume, repetitive tasks. For pick-and-place operations in applications with constrained resources or less rigorous standards, a gantry robot that uses the Arduino Mega 2560 microcontroller and is processed with Python is suitable. Table 1 shows comparisons of robotic systems in terms of important parameters, namely, accuracy, speed, cost and energy efficiency.

Table 2.
Comparison of Robotic Systems on the Basis of Performance Criteria

	Sensor type	**Accuracy**	**Speed**	**Cost**	**Energy Consumption**
Cheng-Yen Chen [20].	Laser Doppler Shift Measurements	high	high	high	low
Sharath GS, Hiremath N [3].	Vision (USB camera)	85-90	Moderate	low	Very low
Judith Doral Vallet al. [19]	Inductive Sensors	High (unspecified)	high	high	Energy efficient and low maintenance
Shubhi Thatere et al [12].	Proximity Sensors	middle	middle	Low moderate	moderate
Freeman et al. [26].	Sensor position (Optical Encoders)	Above 99%	Very high	high	Very Efficient
Janne V. Kujala et al. [27].	Vision(Asus Xtion)	87.5 improving	Fast (<1.8 sec)	high	high
Deyong Shang et al. [7].	vision(Industrial Camera)	72.3% improve	middle	middle	middle
Peng Wang et al. [40].	vision(Visual Servoing System)	90	moderate	moderate	moderate

7. Conclusion

Gantry robots integrate conveyor systems into advanced automated manufacturing settings to form efficient and seamless production lines. This review examines previous studies on gantry robots with conveyor systems and discusses unresolved issues. By reviewing previous studies, we conclude that robots’ use of sensors, vision systems and cameras provides important advantages that help improve the performance of robots and expand their capabilities in various fields. These advantages are summarised as follows:

1. Vision-based systems (including high-speed cameras and LiDAR sensors) can achieve high accuracy in dimension detection; such methods are suitable for tasks that require accurate measurements in dynamic environments.
2. Sensor-based systems employ ultrasonic and infrared sensors and can achieve approximately 85%–90% dimensional accuracy, making them ideal for low-complexity tasks or applications.
3. Structured robotic systems, including Cartesian or gantry robots, exhibit highly accurate movements, and their easy sensor integration contributes to accurate dimension detection.
4. The most relevant software use case that can be employed to achieve high accuracy in dimension detection adopts shelf and high-accuracy robotic stacking algorithms, such as ILC, to refine the system and correct errors during repeated task execution.
5. Data-driven precision refers to the ability of machine learning algorithms, such as CNNs and LSTM networks, to attain increasingly accurate results as they learn from new data consistently, allowing them to enhance system performance with time.
6. Optical and proximity sensors are integrated to cover various dimensions, leading to increased measurement accuracy in dynamic work settings.
7. Integrated systems, such as ROS and PLC, play a role in coordinating hardware components and provide real-time feedback that can improve accuracy and avoid errors during the dimension detection of systems used in the industry.
8. Sensors are less affected by lighting conditions and external environments compared with cameras, making them suitable for harsh industrial conditions. They perform well under various environmental factors, including low light, heat and humidity, and ensure reliable dimension detection in challenging settings.
9. The best plan is a matter of necessity. In the case of maximum accuracy and speed, the ILC gantry robot is the leading tool because it has excellent accuracy and high speed. Garbage-sorting systems regard flexibility and multi-tasking as the main features of dynamic environments, as underlined by AI capabilities. In the case of cost cutting, a gantry robot for unpacking and positioning is a good choice for complex applications, such as feeding and final decision handling. Accuracy, cost and flexibility should be at the same level as the unique requirements of the project. Establishing the distance and location of an object helps. By using a set of sensors, the machine can handle different types of work, thus expanding its flexibility and versatility.
10. The vision and camera technologies used by robots allow them to recognise different kinds of objects and locations by shapes even faster than a human can; thus, they are more efficient in performing tasks. With high-resolution images and videos, they can work exceptionally well in pattern recognition, inventory management and location tracking. The technology also perfectly blends with AI and machine learning, revealing its remarkable potential for system-level integration and dynamic features.
11. The right choice depends on the project requirements, whether it be accuracy, speed, cost, or energy efficiency. Systems that utilise optical encoders deliver a very high accuracy of over 99% and high speed, making them ideal for precision industrial applications. The high price of these systems may, however, discourage some projects. Meanwhile, a system that employs USB cameras provides a compromise between performance and cost, resulting in an accuracy of about 85%–90% at a low cost and low energy consumption. This system is suitable for non-precision applications.

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ايجاد بعد وموقع الجسم في نظام روبوت القنطرة والناقل: مراجعة

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المستخلص

روبوت الرافعة، الذي يُشار إليه غالبًا باسم الروبوت الكارتيزي أو الروبوت الخطي، هو عنصر أساسي في الأتمتة الصناعية المعاصرة. تعمل هذه الأنظمة على طول مسارات خطية، مما يولد مساحة عمل ثلاثية الأبعاد باستخدام العديد من المحاور، بما في ذلك X و Yو Z.تتميز الروبوتات الجسرية بتصاميمها الموحدة، مما يجعلها متعددة الاستخدامات للغاية للعديد من الأغراض. أنظمة النقل الثابت قد أحدثت ثورة في التصنيع من خلال تمكين النقل المستمر والمُؤتمت للموارد. تسهل هذه الشراكة الاختيار السريع للبضائع، والتحديد الدقيق، والنقل المرن لمزيد من المعالجة أو التجميع النهائي، مما يزيد من الإنتاجية والكفاءة التشغيلية. إيجاد الأبعاد المثالية للجسم، والتكوين المكاني، والتحديد الدقيق هي أمور في غاية الأهمية في تصميم الروبوتات الجسرية. التقدم في تقنيات المستشعرات والكاميرات قد عزز بشكل ملحوظ الدقة والفعالية والقدرة على التكيف. قياس الأبعاد ووضع الأجسام هما مهمتان حيويتان تعتمد بشكل كبير على الأنظمة المعتمدة على الرؤية، والتي تشمل الكاميرات عالية الدقة والخوارزميات المتطورة للتحليل المكاني. ومع ذلك، على الرغم من أن هذه التقنيات شائعة في المشهد الحالي، فإن دمج مستشعرات الليزر، وهي خيار محتمل أفضل، لا يزال غير مستكشف بشكل كافٍ. تشير الدقة العالية للغاية للأنظمة القائمة على الليزر في قياس المسافات وتحديد الأجسام إلى مجال للبحث المستقبلي. يتناول هذا المقال التطور التاريخي، والمزايا، والعيوب الخاصة بروبوتات الجسور، مقدماً نظرة شاملة على الإنجازات المعاصرة في تكنولوجيا القياس والتحديد. يوضح المقال مزايا وعيوب عدة طرق استشعار، بما في ذلك الكاميرات، وأجهزة الاستشعار التقليدية، والبدائل الجديدة. على الرغم من التقدم في أنظمة الرؤية لتحديد الهوية وقياس المسافات، لا يزال هناك حاجة إلى حلول مرنة وعالية السرعة يمكن أن تعمل بشكل جيد في البيئات الصناعية الصعبة .