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Review

Current Research Status and Key Technological Advances of Refueling Robots

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Abstract

With the growing global fleet of motor vehicles and rising demand for unmanned services, enhancing the efficiency and intelligence of refueling operations at gas stations has become a critical industry priority. This review focuses on refueling robots as its core research subject, providing a systematic review of its developmental history and system architecture. Building upon this foundation, this review conducts an in-depth analysis and synthesis of three key enabling technologies: (1) the end effector—integrating multi-degree-of-freedom actuators and sensor modules to precisely control fuel tank lid actuation and fuel nozzle insertion/removal; (2) refueling interface identification—enabling vehicle-type classification, refueling interface location extraction, and recognition of refueling interface features; and (3) refueling interface localization—determining the 6 DoF pose of the refueling interface relative to the robot. Through this technical analysis, it is shown that refueling robots have attained an initial level of intelligence; however, significant challenges remain in achieving high precision and robust performance, ensuring safety and reliability, and establishing standardization and broad interoperability. Future research efforts should therefore prioritize improving environmental adaptability—particularly in complex, unstructured settings—advancing autonomous decision-making capabilities, and enhancing product universality, thereby accelerating the commercial deployment of refueling robots.

Keywords: refueling robots; automatic refueling; environmental perception; refueling interface; end effector; recognition and positioning

1. Introduction

Due to the rapid increase in demand for unmanned services, robots are accelerating their transformation from structured industrial scenarios to unstructured service scenarios, demonstrating significant advantages particularly in tasks that are precise, high-risk, hazardous, and repetitive. Consequently, transforming and upgrading vehicle refueling models has become a focal point for the academic community and the industrial sector.

According to the latest data [1], the annual global production of motor vehicles remains at around 90 million units, as shown in Figure 1. By 2020, the global number of motor vehicles exceeded 1.5 billion. China has consistently ranked first in the number of motor vehicles produced for many years, effectively promoting the continuous development of vehicle manufacturing.

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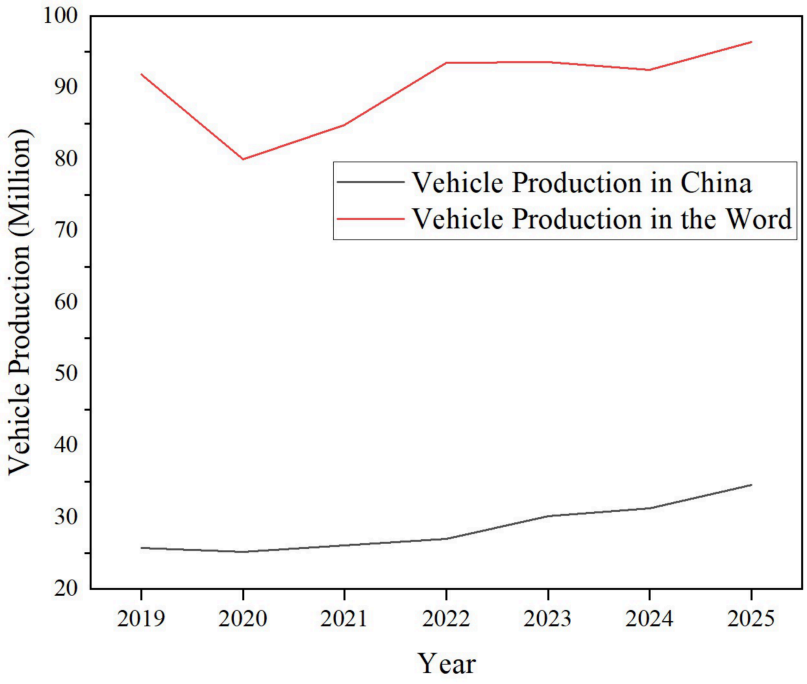


Figure 1. The growth trend of global vehicle production.

Gas stations are crucial venues for supplying vehicles with energy. Currently, fuel dispensing at gas stations relies heavily on manual operations, with two primary refueling modes [2,3]. One is the full-service refueling mode, in which a dedicated refueling attendant guides the driver to park the vehicle in a designated area, inquires about the fuel grade and volume, operates the fuel dispenser to refuel the vehicle, and collects the fuel fee upon completion. The other is the self-service refueling mode, in which the driver parks the vehicle in a designated area, completes the payment through methods such as scan to pay, near field communication, or integrated circuit card, and then operates the fuel dispenser to finish the refueling process. Currently, the full-service refueling mode is the most widely used. As a transitional mode between traditional manual refueling and robotic refueling, the self-service refueling mode has been adopted in Europe and America. However, both of the above refueling modes have the following problems in terms of efficiency, safety, and user experience [4].

The full-service refueling mode has the following drawbacks. In harsh environments such as high-altitude, extremely cold, and high-temperature regions, refueling attendants are unable to perform fuel supply tasks for extended periods. Meanwhile, long-term exposure to harmful oil and gas emissions may pose a risk to their health. Gas stations require attendants to be on duty 24 h a day, 7 days a week, which increases enterprise operating costs. Insufficient staffing leads to congestion during peak hours, resulting in longer waiting times for users. Manual refueling carries risks, including incorrect fuel grade selection, loose fuel filler port, and payment errors. Additionally, there are safety hazards such as refueling with the engine running and failure to eliminate static electricity, which may cause fires or explosions.

The self-service refueling mode has the following drawbacks. Limited by the intelligence level of the refueling equipment, higher requirements are imposed on drivers to operate the refueling equipment independently. Unfamiliar users may reduce overall efficiency and easily cause congestion during peak hours. There are safety risks associated with improper user operation and ambiguities in the definition of accident liability. Meanwhile, refueling equipment is not conducive to operation by special groups such as the disabled, pregnant women, and the elderly.

To address the aforementioned problems, refueling robots have been developed to meet this demand. A refueling robot is an intelligent system that integrates environmental perception, decision-making, control, and safety monitoring. It can independently complete operations such as vehicle guidance, fuel tank recognition and positioning, fuel tank cap opening, fuel gun grasping and insertion, precise refueling, and equipment retrieval without human intervention [5]. Refueling robots offer several advantages, including improved refueling efficiency, reduced labor costs, prevention of refueling with the wrong fuel type, lower risk of fuel spillage, 7 × 24 h unmanned service capability, and suitability for special groups. Additionally, drivers do not need to exit the vehicle in severe weather or during flu outbreaks. The research and application of refueling robots are not only a core means to realize unmanned operation of gas stations, reduce costs and improve efficiency, but also an important measure [6] to build future intelligent transportation infrastructure and provide energy supply services for autonomous vehicles. Furthermore, the rapid development of new energy vehicles has created new application demands for charging robots [7,8] and hydrogen refueling robots [9]. Compared with the refueling robot, the technical architecture of the charging and hydrogen refueling robot is of the same origin as that of the refueling robot. Both consist of systems such as visual perception, decision-making control and safety monitoring.

In the industrial sector [10–12], leading enterprises such as Rotec Engineering, Autofuel, Sinopec and China National Petroleum Corporation (CNPC) have carried out research, development, and commercial application of refueling robots. Although current refueling robots can recognize the fuel tanks of most vehicle models, there are still cases where recognition is inaccurate or impossible for some niche or modified vehicle models, resulting in failed normal refueling operations. In the academic community, significant progress has been made in research on key technologies for refueling robots, including visual perception [10], decision-making and control [11], and robotic arm kinematic analysis [12]. However, the research results primarily address individual technical issues, resulting in a fragmented distribution of these findings. The lack of systematic integration restricts the breakthroughs in their overall performance and large-scale application. At the same time, existing reviews [2–4] on refueling robots focus on analyzing commercial application prospects, but lack a comprehensive review of the overall architecture of refueling robots, the coupling relationships between various modules, key technologies, and challenges, as well as future development directions.

Therefore, this paper conducts a review of the research status of refueling robots. The main contributions of this paper are as follows: This paper summarizes the development stages of refueling robots, which have evolved from the early pure mechanical positioning stage to the non-contact positioning stage based on the collaboration of radio frequency identification (RFID) and distance sensors, and now to the intelligent stage dominated by visual perception. This paper carefully identifies the core technical challenges and bottlenecks faced by refueling robots, from experimental prototypes to commercial applications, and conducts a critical analysis. This paper prospectively identifies potential future research directions for refueling robots, particularly the possible breakthroughs that emerging technologies, such as deep learning, embodied intelligence, and swarm intelligence, may bring.

2. Research Status

2.1. Development Stage

From the perspective of technological evolution, this paper systematically sorts out and summarizes the research progress of refueling robots, and divides the development of refueling robots into three key stages: the mechanical positioning stage (1963–1990),

the RFID and distance-sensor cooperative-positioning stage (1991–2001), and the visual recognition and positioning stage (2002-present), as illustrated in Figure 2.

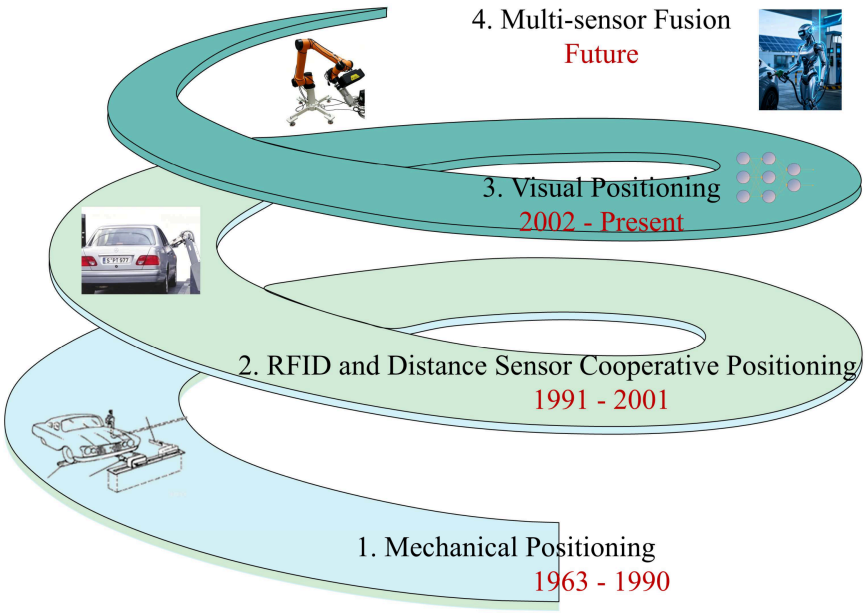


Figure 2. The typical representatives of the refueling robots at each stage.

The first-generation refueling robot, which adopted mechanical positioning, was proposed by Darwin [13] in 1963. This system uses a mechanical positioning mechanism that stops the vehicle's front wheels precisely in the preset grooves. A positioning plate in front of the grooves calibrates the spatial coordinates, which ultimately establishes a mechanical connection between the dedicated refueling gun and the vehicle's fuel tank opening. The first-generation refueling robot required the vehicle to be parked in a designated position. This method has several drawbacks, including complex equipment composition, limited compatibility with vehicle models, and poor positioning accuracy.

The second-generation refueling robot utilizes collaborative positioning technology, incorporating RFID and distance sensors. It realized automatic identification of vehicles to be refueled via RFID by pre-installing on-board identifiers and establishing a pre-built database of user vehicle information. Then, it retrieved data such as vehicle model, fuel type, fuel door location, and fuel cap opening and closing method from the database. Meanwhile, a laser scanner was equipped on the side of the fueling island to assess vehicle position and monitor task progress [14–16]. When a vehicle enters the fueling lane, the feedback signal from the tag received by the RFID reader carries precise distance information. By integrating the phase changes measured by multiple RFID devices, the distance between the reader antenna and the vehicle can be calculated to an accuracy of centimeters. After obtaining the rough positioning of RFID, the distance sensor is used for precise positioning. RFID provides absolute coordinates, and the distance sensor makes relative fine adjustments. Although collaborative positioning using RFID and distance sensors achieved non-contact operation and preliminary automation, it still suffered from several limitations, including a single perception dimension, the necessity of pre-establishing a vehicle data information system and pre-installing RFID chips, limited compatibility with various vehicle models, and low positioning accuracy.

The third-generation refueling robot adopted visual recognition and positioning technology. In 2002, Farag [17] proposed an autonomous refueling system using monochromatic and monocular visual recognition. Cameras and image processing algorithms enabled the system to recognize and position fuel tanks. A decision-making and control system

then guided the robotic arm, forming a closed loop from visual perception to physical manipulation. This stage achieved a technological breakthrough by simulating human functions of perception, decision-making, and execution. As a result, refueling robots began to exhibit primary intelligence. This generation offered high recognition accuracy, fast response, and compatibility with most vehicle models.

In the future, research on refueling robots should shift from a software-defined approach to one that incorporates embodied and swarm intelligence.

The current mainstream refueling robot systems employ deep learning algorithms to train models, and then deploy the offline-trained models onto individual refueling robot systems. However, the deployed systems cannot perform real-time iterative optimization or have feedback correction capabilities, and their ability to generalize to unknown scenarios is weak. In contrast, embodied intelligence enables refueling robots to dynamically perceive the real refueling environment, conduct trial-and-error learning, and achieve iterative optimization. This leads to a leap in development for refueling robots from being software-defined to adaptive decision-making and control. Its core functions are reflected in the following three aspects [18–20]:

The system addresses the constraints of static environments by adapting to complex dynamic scenarios. In situations such as variations in lighting, obstruction of the refueling interface, and misalignment of the vehicle's parking position, the intelligent refueling robot achieves a comprehensive integration of environmental perception, decision-making, and control through the use of multimodal data. For instance, the mechanical arm's movement is automatically adjusted for vehicles that are parked off-center. In cases where the refueling port is obstructed, the operation point is accurately identified by correlating texture features with spatial positioning. Additionally, when personnel and vehicles are in proximity, the mechanical arm's movement is controlled in real time to avoid obstacles.

Establish a secure fault-tolerance mechanism to enhance task robustness. The embodied intelligent refueling robot utilizes a learning mechanism based on perception–action-feedback–iterative optimization, enabling it to receive real-time environmental perception feedback. For example, during the nozzle insertion and withdrawal stages, by leveraging real-time force feedback and employing deep reinforcement learning, compliant docking and separation between the nozzle and the fuel inlet are achieved, preventing equipment damage and fuel leakage caused by rigid collisions.

Enhance the adaptive capability to operating environments, enabling the generalization of refueling robots. Embodied intelligent refueling robots require no large-scale annotated data and, using only a small number of samples, can employ trial-and-error learning and iterative optimization. This allows them to accommodate diverse operational requirements such as variations in fuel tank locations, hatch and cap opening methods, and nozzle insertion torque across different vehicle models, thereby advancing the transition of refueling robots from customized equipment to universal intelligent operational terminals.

Swarm intelligence, from the perspective of system collaboration, overcomes the limitations of individual refueling robots operating independently, inefficiencies of centralized scheduling, and insufficient system fault tolerance, thus promoting the collaborative operation of refueling robots within a gas station. Its core functions are reflected in the following three aspects [21–23]:

Enables dynamic collaboration among multiple refueling robots to improve operational efficiency at gas stations. Through real-time information sharing among multiple agents, swarm intelligence addresses the issue where some refueling robots are idle while others face vehicle congestion and queues.

Swarm intelligence allows refueling robots to adopt decentralized learning, endowing them with independent decision-making, information exchange, and autonomous

fault-tolerant rerouting abilities, thus addressing the low fault tolerance rates caused by traditional centralized control systems at gas stations.

Swarm intelligence enables all refueling robots at a gas station to form a data symbiotic network, allowing features of learned objectives, assembly experience, and abnormal data from each refueling robot to be aggregated and shared in real time, thus resolving the problem of iterative updates for individual refueling robots under traditional deep learning approaches.

In recent years, with the rapid development of visual language models and multimodal foundation models, new research ideas can be provided to enhance the generalization ability of refueling robots [24,25]. By using visual language models, refueling robots can acquire higher-level semantic reasoning capabilities, be able to understand unstructured natural language instructions, improve human–machine interaction capabilities, and achieve the recognition of never-before-seen refueling interfaces. Combining embodied intelligence with visual language models can make the perception, reasoning, decision-making, and execution processes of refueling robots more intelligent. By leveraging the strong zero-sample or few-sample generalization characteristics of the foundation models, without the need for large-scale training data, they can adapt to variable working scenarios. For multi-robot collaborative scenarios, the foundation models can also provide a unified semantic understanding interface for swarm intelligence systems, which is expected to promote the evolution of fueling robots.

2.2. Commercial Refueling Robots

In the realm of commercial refueling robots, a multitude of companies have developed diverse products, among which some have been deeply engaged in the industry for over 30 years while others are high-tech startups. Table 1 lists several currently mature commercial refueling robots along with their core technologies and primary advantages.

Table 1. Several typical commercial refueling robots, accessed on 5 June 2026.

Company	Country	Website	Year	Key Technology	Advantages
Rotec Engineering [26]	The Netherlands	https://rotec-engineering.nl/robotic-fuelling-systems/	2008	single-arm RFID and distance sensors collaborative positioning	The first automatic refueling robot
Autofuel [27]	Denmark	https://autofuel.eu/	2014	single-arm 3D visual	High accuracy Multi-fuel compatibility
Sinopec [28]	China	http://www.sinopecnews.com.cn/xnews/content/2024-02/28/content_7089687.html	2021	dual-arm 3D visual	Refueling cycle time: 120 s Recognition capability: over 500 vehicle models
CNPC [29]	China	https://mp.weixin.qq.com/s/qFZogW9rqoYQ-Tj-fRW4ug	2021	single-arm 2D + 3D visual mobile platform design	Refueling cycle time: 120 s Work envelope: large
AutoEnergy [30]	Sweden	https://autoenergy.se/products/fuelmatics/	2022	single-arm 3D visual	Refueling cycle time: 150 s Multi-fuel compatibility
Yikilometer [31]	China	https://www.1kmxc.com/smoothly.html	2023	single-arm 2D + 3D visual mobile guide rail design	Refueling cycle time: 120 s Recognition rate: ≥90%

Rotec Engineering [26] developed the world's first fully automatic refueling robot in 2008. The system acquires the models of vehicles to be refueled by pre-installing RFID chips on vehicles. It then retrieves information such as fuel types, fuel door positions, and fuel cap opening and closing methods from a pre-established large database. Finally, the robotic arm is controlled to complete the refueling operation. The products of this company have been distributed by Autofuel since 2016.

Founded in 2014, Autofuel [27] identifies vehicle information via RFID to acquire the customer's fuel type and payment data. Not only is it suitable for diesel and gasoline

refueling, but it can also dispense other energy sources—such as electricity, hydrogen, and natural gas—by adjusting the robot's pipelines and end effectors.

Sinopec [28] launched its first dual-arm refueling robot in 2021: one robotic arm is responsible for opening and closing the fuel door and unscrewing/screwing the fuel cap, while the other completes the fuel refueling process. In the same year, CNPC [27] also launched a refueling robot. This system adopts technologies such as 2D + 3D visual recognition and positioning, voice guidance, and a big data cloud platform, enabling functions including online human–machine interaction, intelligent guidance, automatic fuel tank recognition and positioning, and abnormal alarm. Meanwhile, it has been promoted and applied under conditions such as plateaus, frigid regions, and low temperatures.

AutoEnergy [30] merged with Fuelmatics in 2022. The company's refueling robot identifies vehicles and their refueling interface through 3D visual perception, completes fueling within 150 s, and is compatible with gasoline, diesel, hydrogen, electricity, and natural gas. However, it requires vehicles to have specially modified, non-screw-cap fuel tank openings.

In 2023, Yikilometer [31] launched its developed energy arm, which adopts a mobile guide rail design, and expands its working reach. Through an online incremental learning mechanism, the system continuously collects data on vehicle models and refueling interface in actual operations, enabling online updates of model parameters.

As shown in Table 1, research on commercial refueling robots has shifted from a hardware-dependent approach to an initial stage of data-driven intelligence. Refueling robots typically take two to three minutes, whereas traditional manual fueling takes five minutes. Therefore, using refueling robots significantly improves fueling efficiency. The refueling robots from Autofuel and AutoEnergy are compatible with various fuel types. Only the necessary energy pipelines need to be replaced during use to achieve the product's universality. Although significant progress has been made in the research of commercial refueling robots, problems remain, such as the low accuracy of fueling interface recognition, the variety of fueling interface types, and the absence of relevant regulations.

According to our investigation, the specific installation sites of the above commercial robots are unknown; only some pilot operation cases could be identified. For example, the refueling robot developed by Sinopec has been piloted at seven gas stations in Hunan and Anhui, among other locations, cumulatively refueling over 1800 vehicles with more than 2600 refueling operations [28]. The barriers to large-scale commercial deployment stem from technical, economic, regulatory, and operational dimensions. On the technical front, due to the diversity of refueling interface and the lack of a refueling interface dataset, current algorithms cannot yet detect and recognize the refueling interface of all vehicle models. Economically, the prices of robotic arms, vision sensors, and control systems remain high, prolonging the payback period for operators. From a regulatory perspective, there are not yet clear regulations specifying the responsibilities of the parties involved regarding safety risks, such as collisions, fires, and explosions that may occur during the robot's operation. Operationally, most users are only conceptually aware of refueling robots, and initial deployment requires on-site assistance from professionals. The motivation for discussing this section in the review is to systematically analyze the deployment obstacles faced by refueling robots and assess the potential contributions of academic research in bridging this gap.

3. System Composition and Key Technologies

3.1. Working Process of Refueling Robots

Taking the refueling robots fixed on fueling islands as an example, this section presents the workflow diagram of refueling robots, as illustrated in Figure 3. When a vehicle

requiring refueling enters the gas station, it is guided to the fueling lane and position designated for the refueling robot. This guidance is provided via voice prompts and physical signs. Visual detection then verifies whether the vehicle is within the robot's operational range. After parking at the specified position, the user selects the fuel type and volume via a mobile app, settles the payment, and unlocks the fuel tank. Upon receiving the refueling command, the refueling robot activates its environment perception module. It identifies the fuel door and locates the fuel cap and filler port. The decision-making and control module then executes task planning, path planning and motion planning for the operation. The robot manipulates the gripper and vacuum suction cup to open the fuel door and cap. It then inserts the fuel nozzle for refueling. After the refueling process, the robot closes the fuel cap and door using the same tools. During the operation, multiple sensors detect potential risks, such as collisions, oil–gas concentration exceeding safe limits, and mechanical overload.

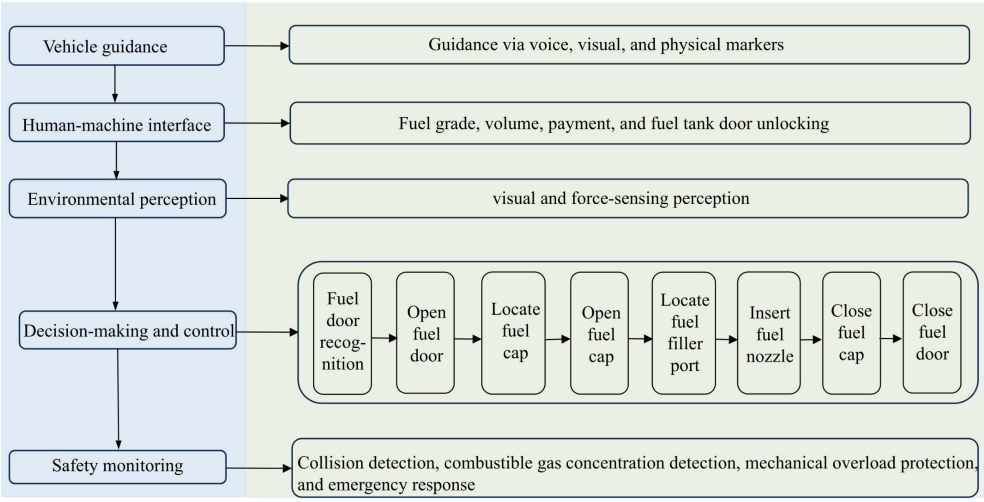


Figure 3. Working process of refueling robots.

3.2. System Composition of Refueling Robots

Based on the analysis of the refueling robot workflow, to complete refueling operations as quickly, accurately, and safely as manual refueling, a refueling robot must be equipped with capabilities of perception, analysis, reasoning, decision-making, and execution. Therefore, a refueling robot needs to consist of a human–computer interaction module, an environment perception module, a decision-making and control module, an execution module, and a safety monitoring module [4,32,33], and its system composition is illustrated in Figure 4.

The decision-making and control module serves as the brain of the refueling robot. It is endowed with functions including task planning, path planning, motion planning, and visual servo control. First, it generates a task list based on user requirements. Then, it plans the optimal motion path of the robotic arm according to the pose coordinates of the refueling interface output by the environment perception module. It also generates the functional relationships of velocity and acceleration of each joint over time. Finally, it controls the movement of the robotic arm and adjusts the end-effector pose in real time based on visual or force feedback [11]. Its core function is to convert environmental perception data into robotic arm movement, dynamic obstacle avoidance, and compliant docking.

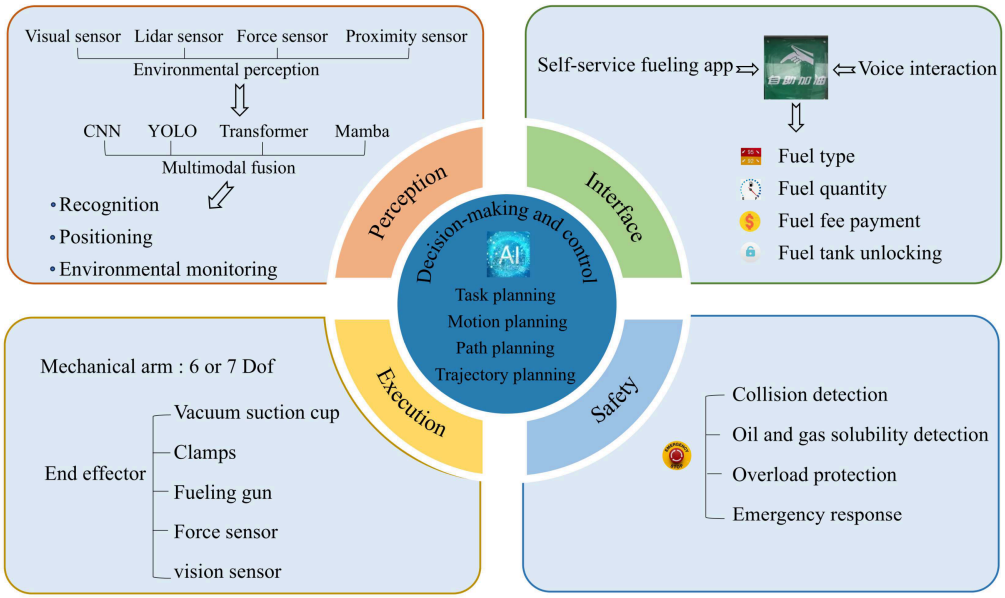


Figure 4. System composition of refueling robots.

The environmental perception module serves as the refueling robot's eyes, providing visual and force perception capabilities [4]. It is composed of RGB/RGB-D cameras, LiDAR, force sensors, proximity sensors, and more. As shown in Table 2, the sensor components of some of the cited references are listed. It can be seen from the table that RGB sensors are predominantly used in fuel nozzle recognition tasks. In fuel nozzle recognition and localization tasks, both RGB and RGB-D multimodal data are employed: RGB data provides the appearance features of the fuel nozzle, while RGB-D data is used to provide geometric information of the fuel nozzle. However, the relevant literature does not specify the fusion strategies for these two different modalities, such as early fusion, late fusion, or cross fusion. In addition, there are no reports yet of using millimeter wave radar or lidar for fuel nozzle recognition and localization.

Table 2. Sensors used in the research on refueling robots.

Reference	Year	Sensor	Task	Actuator	Platform	Scenario
Yikilometer [31]	2023	RGB RGB-D Force sensor	Recognition and Positioning	Single 6-DoF manipulator	Mobile	Commercial vehicles
Sinopec [28]	2021	RGB RGB-D Force sensor	Recognition and Positioning	Dual 6-DoF manipulators	Stationary	Commercial vehicles
Liu et al. [34]	2023	RGB-D Force sensor	Recognition and Positioning	Single 6-DoF manipulator 6	Stationary	Special vehicles
Yang at al. [10]	2024	RGB-D	Recognition and Positioning	Single 6-DoF manipulator	Stationary	Special vehicles
Zhang et al. [35]	2025	RGB	Recognition	-	-	Commercial vehicles
Zhang et al. [36]	2021	RGB	Recognition	-	-	Commercial vehicles
Fu et al. [37]	2024	RGB	Recognition	-	-	Commercial vehicles

The execution module consists of a robotic arm and an end effector. The robotic arm is typically an industrial arm with six or seven degrees of freedom. The end effector consists of a vacuum suction cup, a gripper, and force and vision sensors. The execution module's core function is to convert the decision control module's task planning into reliable mechanical movements that open and close the fueling interface, enable flexible docking, and facilitate fueling and retraction [5,38,39].

The safety monitoring module is equipped with functions such as collision detection, oil spillage detection, and mechanical overload protection [40]. The real-time data collected

by the environmental perception module allows the module to make decisions regarding risks such as mechanical collisions, oil solubility, and vehicles driving away with guns. The safety monitoring module can immediately shut down the machine upon a request for manual intervention, providing all-weather and all-scenario safety guarantees for refueling operations.

The human–computer interaction module is composed of sub-modules, including the self-service refueling APP [41–43], voice interaction, transaction management [44], status indicator lights, and emergency stop buttons. Its core function is to provide intuitive operation guidance through graphic and textual or voice prompts, display real-time information such as fuel type, payment progress [45,46], refueling progress, and fault alarms [47], and support functions including one-click emergency stop, emergency avoidance, emergency intervention, and remote control management [48]. This ensures that both novices and professionals can complete the refueling operation safely, efficiently, and independently.

There is significant heterogeneity in explosion hazard zones within gas stations, so equipment hardware must comply with the corresponding explosion-proof grade. Therefore, sensors are restricted by intrinsic safety power limits, heat dissipation, and wiring standards, which in turn limits imaging and perception performance. Computing units are housed in explosion-proof enclosures, leading to bottlenecks in heat dissipation and transmission bandwidth. Control components may decrease the response speed of motion control. To meet explosion-proof measures, it is often necessary to accept reduced performance and increased latency. The conflict among safety, performance, and real-time capability can be alleviated through optimization strategies such as hierarchical intrinsic safety and explosion-proof hardware architectures, lightweight perception models, vision-force closed-loop collaboration, and enhanced cabinet heat dissipation.

3.3. The Refueling Interface and End Effector

The refueling interface and end effector are the core components of a refueling robot for fuel replenishment of vehicles. The refueling interface determines the type of the end effector, while the end effector dictates the reliability, efficiency, and versatility of the entire system.

The refueling interface consists of the fuel door, fuel cap, fuel filler port, etc. The fuel door refers to the external cover plate installed on the vehicle body. The fuel cap refers to the internal threaded sealing cover. The fuel filler port refers to the connection point where the fuel nozzle and the fuel tank are inserted and interlocked with each other. It serves several functions, including mechanical protection, danger interruption, and oil vapor recovery. Its role has evolved from that of a simple physical connection to that of a component that integrates safety, efficiency, and intelligence. This paper classifies refueling interface as either traditional or dedicated. Traditional interfaces are divided into two categories: those with and without screw caps. Those with screw caps are used for common car brands. Those without screw caps are commonly used for Ford vehicles and were originally proposed by Ford. Dedicated refueling interface usually have self-sealing mechanisms and are used for specialty vehicles, as shown in Figure 5. They adopt a multi-level interlocking sealing design consisting of a male connector and a female connector. The male connector is typically installed on the fuel tank, while the female connector is installed on the end effector. Once rotated into place, the valve automatically opens; once separated, the valve automatically closes [10].



(**a**) Threaded fuel filler port (**b**) Capless fuel filler port (**c**) Self-sealing connector

Figure 5. Three typical types of fuel filler port.

The end effector is the execution mechanism through which the refueling robot interacts with the vehicle. Its level of intelligence directly determines the reliability and efficiency of the system. The end effector is composed of vision cameras, force sensors, vacuum suction cups, grippers, screwing motors, and linear push rods, and is equipped with functions such as recognition and positioning, fuel cap opening, fuel nozzle insertion, fuel cap closing, as well as perception and feedback, as shown in Figure 6. This end effector adopts an integrated design, featuring simplicity in structure and ease of deployment. However, it has the disadvantages of being large, having limited movement space and poor flexibility [29]. Some designs employ dual-arm robots, integrating the functions of opening the fuel door and screwing the cap into one mechanical arm, while the other arm is used for grasping and inserting the fueling nozzle. This design has the advantages of parallel task processing, large working space, and high flexibility. However, it has a relatively high overall cost, and the control of the coordinated movement of the two arms as well as the task allocation are rather challenging [28]. Different types of end effectors must be used for various refueling interface to complete corresponding refueling operations.

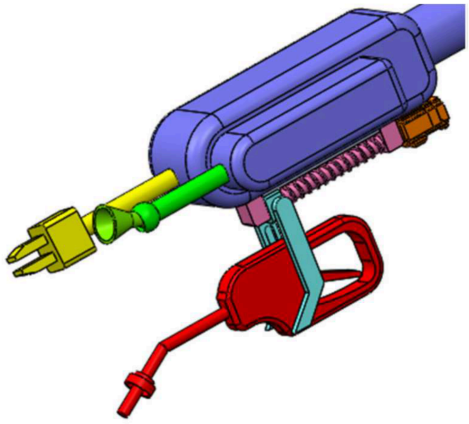


Figure 6. End effector [38].

When a screw-cap refueling interface is used, the robot must perform several operations. These include opening the fuel door, unscrewing the fuel cap, grasping the fuel nozzle, and inserting it into the fuel filler port, as shown in Figure 7. The robot must also close the fuel cap and the fuel door. A clamping device and a rotating motor are required to unscrew the rotating cap, as opposed to the refueling interface without screw caps and the dedicated filling interface. This end effector has an integrated design with the advantages of a simple structure and convenient deployment. However, it is large in size and has limited movement space and poor flexibility.

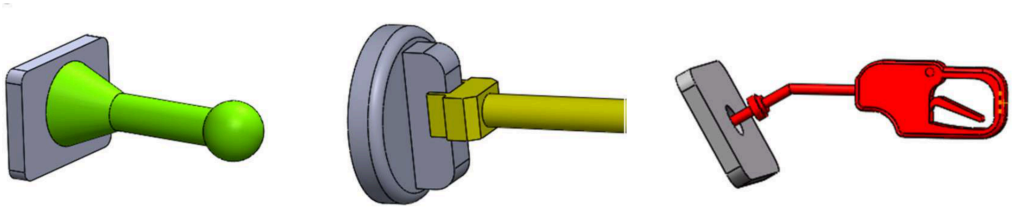


Figure 7. The connection process [38].

When a capless refueling interface is used, diameter is usually larger than the fuel nozzle. As a result, positioning and angular orientation requirements are less strict. This reduces the difficulty of automatic docking and eliminates the need for precise compliant control. However, this setup has drawbacks. This leads to a low refueling speed, poor oil vapor recovery, and an increased fire risk from fuel spillage.

When a capless refueling interface is adopted, the robot must control the end effector to perform operations such as opening the fuel door, grasping the fuel nozzle, inserting it into the fuel filler port, and closing the fuel door, as illustrated in Figure 8. This interface eliminates the need for unscrewing and tightening the threaded cap, instead using a self-opening cover mechanism as a replacement for the screw cap. Therefore, the end effector does not need to be equipped with a gripper and a screwing motor, which reduces the complexity of end execution as well as the difficulty of task planning and motion control, as shown in Figure 9. The fuel filler port without a twist-off cap allows only fuel nozzles of the corresponding fuel type to be inserted, preventing incorrect refueling and enhancing theft prevention. Vehicles equipped with capless refueling interface feature standardized refueling ports, thereby reducing the difficulty of adaptation for robot end effectors. However, the need for compatibility between the fuel filler port and the fuel nozzle model imposes stringent requirements for positioning and angular orientation accuracy. As a result, precise compliant control is necessary to apply thrust smoothly, overcome the spring resistance of the baffle and locking plate, and achieve compliant docking. Meanwhile, this type of interface may encounter difficulties with fuel nozzle extraction during actual operation.

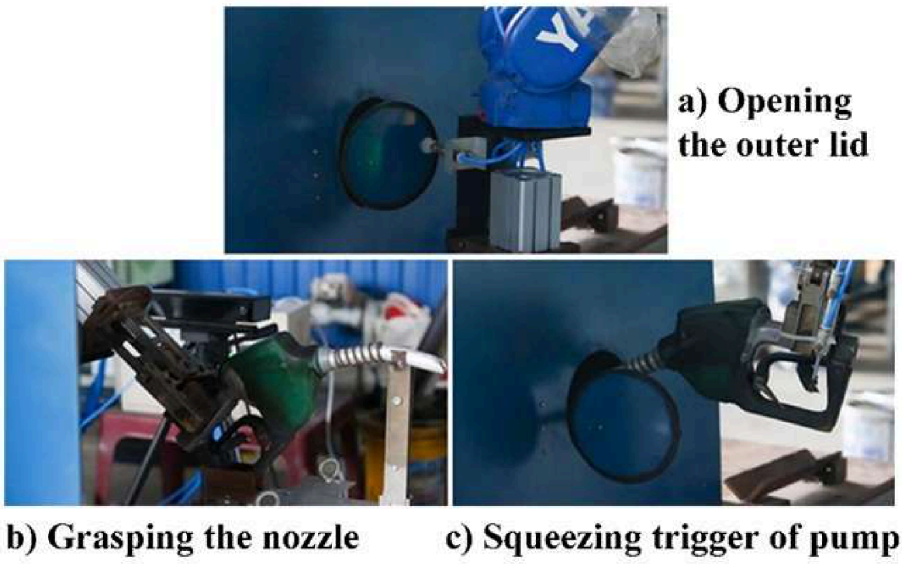


Figure 8. Docking process of capless fuel tanks [49].

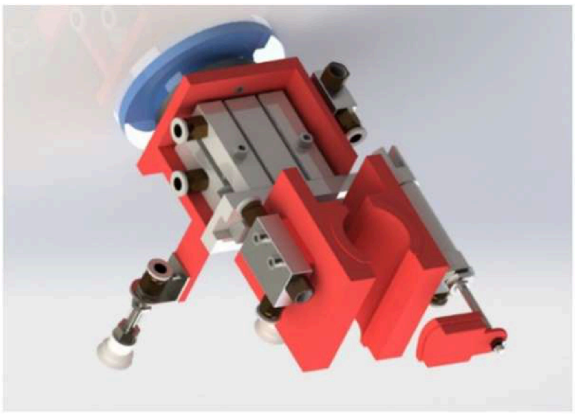


Figure 9. End effector for capless fuel tanks [49].

When a dedicated refueling interface is adopted, the robot only needs to perform two operations: insertion and rotation. As a result, there is no need to equip it with a vacuum suction cup or a gripper. Consequently, the end effector features the simplest structure [10], as illustrated in Figure 10.



Figure 10. The process of connecting through the dedicated refueling interface [10].

The dedicated refueling interface eliminates fuel spillage, increases the recovery rate of fuel vapors, and enhances refueling speed. It allows for instantaneous connection and disconnection and can seal or dislodge the interface in milliseconds. When using the dedicated refueling interface, the axes of the male and female connectors and the three slots must be aligned. The positioning error requirements for the position and angle are high, and the flexible connection is difficult.

3.4. Refueling Interface Recognition and Positioning

LiDAR is more resistant to interference from light, rain, fog, and dust than RGB-D cameras are. However, LiDAR's accuracy is only at the centimeter level, and the generated point cloud is sparse. This makes it difficult to precisely reconstruct small parts, such as the refueling interface. RGB-D cameras, on the other hand, can achieve sub-millimeter accuracy and generate dense point clouds. This allows for precise reconstruction of the refueling interface's geometric structure and guides the mechanism to complete a smooth docking. Identifying and positioning the refueling interface requires more than just ranging; it also requires calculating the 6D pose coordinates of the interface with high precision relative to the camera. Therefore, vision is still given priority in the development of refueling robots. Thus, this paper focuses on analyzing and summarizing the recognition and positioning of refueling interface using RGB or RGB-D technology.

3.4.1. Refueling Interface Recognition

The recognition and detection of the refueling interface obtains its specific position in the image. This allows us to crop the corresponding pixel area for the subsequent pose estimation task. This reduces computational cost and improves efficiency. This section introduces the current state of research on recognizing and detecting the refueling interface based on machine learning and deep learning.

Refueling Interface Recognition Based on Machine Learning

During the machine learning stage, recognition of refueling interface relies on human-designed detection operators based on the interfaces' shapes, colors, and textures. However, the algorithm's accuracy and generalization ability are poor. Zhang et al. [50] combined morphological gradient and Hough transform to detect and recognize fuel door under mirror reflection conditions. Liang et al. [51,52] combined the Canny algorithm, histograms of oriented gradients (HoGs), and a SVM classifier to improve the robustness of fuel door recognition in unstructured environments. Chen et al. [53] proposed an improved speeded up robust features (SURF) algorithm. By preprocessing images through alpha filter correction and gamma correction, combined with KD-tree search and random sample consensus strategies, the accuracy of fuel door recognition was increased from 79.3% to 92.7%, and the average time consumption was reduced by 19.2%. Lam et al. [49] employed the Douglas–Peucker algorithm to approximate the fuel door contour as a polygon with a specified accuracy, thereby reducing the number of contour points required for polygon approximation of the contour. Li et al. [54] proposed a fuel door detection algorithm based on multimodal features and SVM fusion, achieving a detection accuracy of 99%. Nevertheless, this algorithm relies on manually designed features and has insufficient generalization ability in unstructured scenarios.

Table 3 summarizes the research findings on refueling interface detection and recognition based on machine learning. The datasets used in the literature are all private datasets owned by individuals, rather than unified open-source datasets. As can be seen from the table, existing studies have achieved remarkable progress in detection and recognition accuracy, yet several technical issues remain to be urgently addressed. In terms of algorithm robustness, some algorithms lack sufficient generalization capabilities in complex environments, such as those with oil contamination, specular reflection, strong light, and low-light conditions. In terms of algorithm real-time performance, the high computational complexity of feature descriptors and the high-dimensional feature matching mechanism make it difficult for the algorithms to meet the real-time requirements of embedded platforms or dynamic tracking scenarios. In terms of scenario universality, all existing studies only focus on the detection of a single category, either fuel door or fuel cap. In terms of feature engineering, the adoption of manually designed features in existing methods results in a poor autonomous learning capability of the networks.

Table 3. Research achievements on the detection of refueling interface based on machine learning.

References	Year	Target	Algorithm	Accuracy	Advantages	Limitations
Zhang et al. [50]	2018	Fuel door	Image morphology, Hough	81%	Exhibits good suppression of illumination and angle variations	Low accuracy
Liang et al. [51]	2021	Fuel door	Otsu, Canny	—	Improve the robustness and accuracy of edge detection	High algorithm complexity and poor real-time performance
Lam et al. [49]	2021	Fuel door	Douglas–Peucker	—	Analyzed the effects of distance and angle on the results	Only applicable to capless fuel tanks

Table 3. *Cont.*

References	Year	Target	Algorithm	Accuracy	Advantages	Limitations
Liang et al. [52]	2022	Fuel door	HoG, SVM	96.22%	Improved the robustness and accuracy	Inferior real-time capability
Chen et al. [53]	2023	Self-sealing connector	SURF	92.7%	Reduced the false matching rate of feature points	Inferior real-time capability
Li et al. [54]	2024	Fuel door	SVM	99%	Improved the detection accuracy of weak textures and specular reflections	Inadequate robustness under complex conditions

Refueling Interface Recognition Based on Deep Learning

Different from machine learning algorithms, deep learning enables the creation of more abstract and high-level feature and attribute categories, thereby improving the accuracy of target detection and recognition. Deep learning-based algorithms for refueling interface detection and recognition are classified into one-stage and two-stage algorithms according to the inference phase. Faster R-CNN [55] is a typical two-stage detection algorithm, which first generates region proposals and then performs classification and regression on these proposals. Its advantage lies in high accuracy, while its disadvantages are large computational complexity and poor real-time performance. Zhang et al. [36] proposed an improved Faster R-CNN algorithm based on ResNet-101 for fuel door detection, achieving a detection accuracy of 98%, which is significantly superior to the backbone networks based on VGG16 [56] and YOLOv3 [57]. However, the detection accuracy of the algorithm drops to 87.05% for fuel door with complex textures, and its generalization capability is insufficient under extreme illumination or occlusion scenarios. Ma et al. [58] proposed an improved Faster R-CNN algorithm for fuel door detection, building upon the work of Zhang et al. [36]. By optimizing the generation strategy of the region proposal network to adapt to the geometric characteristics of the target, the recognition accuracy is increased to 98.53%.

To address the limitations of two-stage detection algorithms, YOLO [59] employs a one-stage detection algorithm that eliminates the need for region proposal generation, instead directly predicting bounding boxes and categories on images. Li et al. [60] introduced an attention mechanism based on YOLOv5 to optimize the network, achieving an improvement of 0.5% in mAP compared to YOLOv5. Fu et al. [37] modified the feature fusion network and incorporated the C2f-Faster module based on YOLOv8, which reduced the number of network parameters by 56.95% and computational complexity by 37%, while achieving a detection accuracy of 99.5%. Qiao et al. [61] proposed the FastVim-YOLO, which optimizes YOLOv8n by introducing FastViT and Mamba modules. Compared with YOLOv8n, it achieves a 2.1% improvement in mAP@50, reduces the parameter count by 38% and the computational cost by 59.2%, and increases the inference speed by 44%. Zhang et al. [35] presented the BES-YOLO detection algorithm by embedding the BiFPN and effective attention mechanism module. This algorithm achieved a recognition accuracy of 98.2% under complex scenarios, such as low illumination and dust occlusion, with its mAP@50 increasing to 99.2%—a 0.2% improvement compared to YOLOv8n. Dai et al. [62] based on YOLOv8n, replaced the original backbone network with StarNet, and then replaced the C2f module in the original network with the C2f-Faster module. The improved algorithm was named SL-YOLO. Compared with YOLOv8n, its mAP50 increased by 0.6% and the accuracy rate reached 98.7%.

Table 4 summarizes the research results on deep learning-based detection and localization of refueling interface. As can be seen from the table, the deep learning-based methods for refueling interface detection and recognition outperform the machine learning-based methods in both accuracy and detection time. Deep learning has increasingly replaced

traditional machine learning algorithms that rely on manually designed features. Deep learning-based algorithms mainly adopt Faster R-CNN and YOLO as the backbone networks for feature extraction, which extract the semantic information of images from shallow to deep layers, enable the networks to autonomously learn target features, and thus improve the accuracy and generalization ability of the networks. It is worth noting that the current algorithm only supports the recognition of fueling ports under static conditions. Further research is needed for the recognition of fueling ports under dynamic conditions.

Table 4. Research achievements on the detection of refueling interface based on deep learning.

References	Year	Target	Algorithm	Accuracy	Time	Advantages	Limitations
Zhang et al. [36]	2021	Fuel door	Faster-RCNN	98%	139 ms	Innovative model architecture	Low detection accuracy for fuel door with complex textures
Ma et al. [58]	2022	Fuel door	Faster-RCNN	98.53%	170 ms	High real-time performance and accuracy	Insufficient generalization capability
Li et al. [60]	2023	Fuel door	Yolov5	93.8%	——	The introduction of the attention mechanism	Insufficient training data
Fu et al. [37]	2024	Fuel door	YOLOv8	99.5%	8.1 ms	High detection accuracy	Inadequate consideration of special scenarios
Qiao et al. [61]	2025	Fuel door	FastVim-YOLO	94.2%	5.68 ms	Strong global modeling capability of the network	Low detection accuracy
Zhang et al. [35]	2025	Fuel door	BES-YOLO	98.2%	——	Model lightweighting	Inferior real-time capability
Dai et al. [62]	2025	Fuel door	SL-YOLO	98.7%	4.18 ms	Enhance the detection capability for small targets	Insufficient generalization capability

The refueling interface recognition algorithms in the literature investigated so far all use RGB images as input data, resulting in low recognition accuracy under challenging conditions such as lighting variations, occlusion of the refueling interface, and changes in angle and position. However, as RGB-D sensors become more affordable and deliver superior performance, future research may employ multimodal fusion to input both depth and RGB images into the model during training. This approach will not only improve the accuracy of refueling interface detection and recognition but also enhance the precision of subsequent pose estimation.

Furthermore, in static scenarios, the refueling interface and camera remain relatively fixed. However, in dynamic scenarios, camera imaging can produce motion blur, viewpoint changes may result in partial occlusion in captured images, and the recognition and localization time for the fuel interface may exceed the dynamic response requirements of the robotic arm. To address motion blur, a combination of hardware control and adaptive algorithms can be employed to improve image quality. For viewpoint changes, key point detection can be used as a substitute for contour detection of the fuel interface. To address real-time performance, lightweight recognition and localization algorithms can be adopted, and multimodal algorithms can be used to fuse visual and force data, thereby eliminating visual latency. In practical engineering applications, backbone networks with high real-time performance include MobileNetV3 [63], ShuffleNetV2 [64] and YOLOv8 [65], etc.

3.4.2. Refueling Interface Positioning

The purpose of the refueling interface recognition is to obtain its pixel coordinates on the image. However, the purpose of the refueling interface positioning is to obtain its 6D pose relative to the robot. After the refueling robot obtains the real-time pose coordinates of the refueling interface, it manipulates the robotic arm to make the end effector reach directly

above the refueling interface. During the insertion process, the end position is adjusted by force feedback to achieve a smooth docking. The pose estimation of the refueling interface involves coordinate transformation, as shown in Figure 11. The camera coordinate system (O_c), the end-effector coordinate system (O_e), the refueling interface coordinate system (O_o), and the world coordinate system (which is usually in alignment with the robot base coordinate system) are established. The end-effector coordinate system takes the center of the negative end of the refueling interface as the origin and defines the feed and clamping postures during the docking process; the camera coordinate system is established based on the camera optical center, and the RGB image and three-dimensional point cloud are projected to the camera space through camera internal parameter calibration; the refueling interface coordinate system serves as the geometric reference for docking, and its relative rigid body transformation matrix to the camera space is solved through the pose estimation algorithm. By using hand–eye calibration to obtain the transformation relationship between the camera and the robot, the visual perception is converted into executable motion control instructions for the robotic arm.

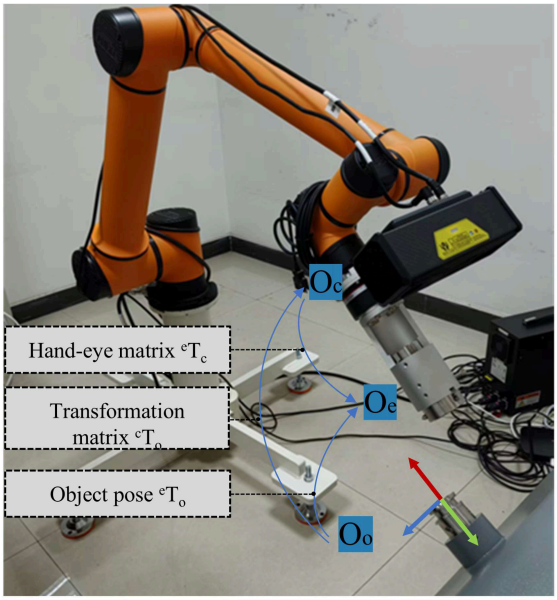


Figure 11. The docking position coordinate system of the refueling robot.

Similar to the development trajectory of 2D target detection and recognition algorithms, target pose estimation has also evolved from traditional methods centered on manually designed features in the early stage [66,67] to deep learning-based methods [68–71]. Currently, target pose estimation methods are categorized into instance-level, category-level, and unseen-level approaches. Instance-level methods can only infer the pose of specific instances, category-level methods can infer the pose of objects within the same category, and unseen-level methods can infer the pose of objects from categories that have never been encountered [72]. For refueling robots, only the detection and localization of refueling interface are required, so the adoption of instance-level methods is sufficient to meet application requirements. Instance-level pose estimation methods can be classified into iteration-based, key point-based, template matching-based, and regression-based methods [73].

Iteration-based methods optimize the pose to minimize the error between the object model rendered by CAD and the real target model [74]. Xie et al. [75] proposed an IM-AEPCI algorithm for fuel door pose estimation based on 2D-3D fusion. This method utilizes an adaptive exposure prediction network (AEP-Net) to generate the target point cloud, then employs the iterative closest point (ICP) algorithm to achieve point cloud registration, and

finally achieves millimeter-level pose localization of the fuel door, with the entire process taking only 5 s. Hou et al. [76] constructed a hash table using point pair features (PPF), quickly estimated the initial pose through feature discretization and a voting mechanism, then iteratively optimized the coarse registration results via ICP, and finally solved the target pose through nearest neighbor search and rigid body transformation.

Key point-based methods detect 2D sparse key points of the target through the network, and then use the Perspective-n-Point (PnP) algorithm to solve the target pose [77]. Wang et al. [78] proposed a coarse-to-fine pose estimation method for fuel door. First, they used binary robust independent elementary features (BRIEF) to describe target edge point pairs and obtain coarse registration point pairs. Then, they adopted the random sample consensus (RANSAC) algorithm to screen out matching point pairs that satisfy consistency constraints, with the entire process taking only 165 ms. Liu et al. [34] combined the Hough transform and Shi–Tomasi corner detection, achieving a positioning accuracy of ± 1 mm and an angular error of $\pm 1^{\circ}$, which effectively improved the robustness of pose estimation. Yang et al. [10] proposed a dedicated refueling interface pose estimation method based on RGB-D vision guidance. By fusing YOLOv8 and the Perspective-n-Point algorithm to solve the pose, the average docking time was reduced by 6.9% compared with the traditional OpenCV method.

Template matching-based methods match the most similar template from a set of templates with annotated poses [79]. Template-based methods utilize the global information of images, which can effectively address the challenges posed by textureless objects. Bian et al. [80] proposed a coarse-to-fine template registration and pose correction strategy for the pose estimation of fuel tank caps. In the coarse registration stage, the intrinsic shape signatures (ISS) algorithm was adopted to extract 3D key points from the point cloud edges; in the fine registration stage, principal component analysis (PCA) was performed on the point cloud, and through geometric feature matching and coordinate axis alignment optimization, a position error of ± 1 mm and an angular error of $\pm 2^{\circ}$ were finally achieved. Ma et al. [58] employed the semi-global block matching (SGBM) algorithm and the AD-Census stereo matching algorithm to generate disparity maps. They then calculated the physical distance and 3D coordinates of the object and optimized mismatched points using the bilinear interpolation method. Chen et al. [53] proposed an improved semi-global matching (SGM) algorithm, which first detects the center of the interface circle using the Hough transform and then combines it with the RANSAC algorithm to achieve a position error of ± 2 mm and an angular error of $\pm 2^{\circ}$.

Table 5 summarizes the research results on refueling interface pose estimation, detailing the input data type, positioning error, core algorithm, method category, and other contents. As can be seen from the table, existing studies primarily employ iterative optimization, key point detection, and template matching for refueling interface pose estimation. The input data types include RGB, depth map, and RGB-D, among which RGB-D dominates. It can better utilize the geometric information of objects provided by depth maps to achieve high-precision pose estimation. Existing studies reveal significant differences in terms of accuracy and efficiency: iterative optimization methods exhibit excellent accuracy but high computational complexity; key point detection methods perform well in real time but are sensitive to texture features; template matching methods have advantages in handling textureless objects, but require pre-generating a template library. Although existing studies have made progress in accuracy, real-time performance, and robustness, they still face challenges such as light sensitivity, high computational complexity, and strong model dependence.

Table 5. Research results on the pose estimation of refueling interface.

References	Year	Input data	DoF	Positioning Error	Key Algorithm	Classification
Ma et al. [58]	2022	RGB Depth	6	——	SGBM, AD-Census	Template matching
Bian et al. [80]	2022	RGB-D CAD Model	6	Position error < ±1 mm Angular error < ±2°	ISS, PCA	Template matching
Wang et al. [78]	2023	RGB Depth	6	Absolute Position Errors of X, Y, Z: 15, 15, 5 mm	BRIEF, YOLOv3, RANSAC	Key point
Chen et al. [53]	2023	RGB Depth	6	Position error < ±2 mm Angular error < ±2°	SGM, Hough, RANSAC	Template matching
Liu et al. [34]	2023	RGB-D	6	Position error < ±1 mm Angular error < ±1°	Hough, Shi–Tomasi	Key point
Xie et al. [75]	2023	RGB RGBD	6	Position error < ±1.8 mm Angular error < ±1.05°	AEP-Net, ICP	Iteration
Yang et al. [10]	2024	RGB-D	6	——	YOLOv8, PnP	Key point
Hou et al. [76]	2024	RGB-D	6	Position error < ±0.3 mm Angular error < ±0.02°	PPF, ICP	Iteration

In the references surveyed thus far, while most studies use RGB-D as input data, some traditional algorithms are still adopted for pose estimation, such as PPF, Shi–Tomasi, Hough, etc. Other studies employ two-stage algorithms, where recognition algorithms are first used to detect the refueling interface location on the RGB image, and the corresponding regions on the RGB and Depth images are cropped and then sent to the subsequent pose estimation module for training. These algorithms exhibit poor real-time performance and require extensive post-processing; future research could employ end-to-end networks that directly output the pose of the refueling interface.

3.5. Compliant Control Between Fuel Nozzle and Fuel Filler Port Based on Force Feedback

The coarse positioning of the refueling interface can be achieved through the visual method in Section 3.4. However, due to factors such as the positioning error of the robotic arm, the positioning error of visual recognition, and the error of camera calibration, there are unavoidable positioning errors in the pose of the refueling interface. Moreover, in an unstructured environment, the differences in the structure and size of refueling interfaces of different vehicle models lead to non-linear, time-varying and unpredictable contact forces. Additionally, there is a risk of fuel leakage during the docking process, and repeated trial and error is not allowed. Therefore, using force feedback-based compliant control is an effective solution. It can avoid rigid collisions between the fuel nozzle and the fuel port, thereby reducing safety hazards such as oil and gas leakage and fire. The docking of the fuel port and the fuel port is a typical peg-in-hole assembly task, where the fuel nozzle represents the peg and the fuel port represents the hole. Visual recognition positioning realizes hole search and peg-in-hole alignment, and force feedback is used in the insertion stage.

Currently, after investigation, it has been found that there are no reports on the compliant control of refueling robots in the existing literature. However, hydrogen refueling robots and charging robots belong to the same type of peg-in-hole assembly tasks, such as having small assembly gaps and strict contact force restrictions. First, visual methods are used for coarse positioning, and then the end position of the robotic arm is finely adjusted through force feedback to achieve compliant docking. These highly related research results in task scenarios can provide theoretical and technical references for the research on the compliant docking of refueling robots. As shown in Table 6, it is divided into passive compliant control and active compliant control. Passive compliant control is designed based on specific application scenarios to incorporate specific mechanical devices to absorb contact forces, but it lacks the ability to actively correct deviations. Lou et al. [81] designed a 4 DoF cable-driven charging robot, and the end effector used a flexible plug that could withstand small elastic deformations. Impedance control establishes the dynamic relationship between the end position deviation and the contact force through a mass–spring–damper model, and adjusts the robot's impedance to achieve compliant

control. In the hydrogen refueling robot, a hybrid force-position framework was adopted, separating trajectory tracking from contact force constraints during the nozzle insertion process to ensure that the contact force remains within the safe range [82]. Additionally, a multi-scale perception and docking control strategy for task decoupling was proposed to adapt to the dynamic contact state changes during the insertion process [83]. In the charging robot, after visual coarse positioning, the robotic arm adjusts the end effector's posture in real time based on the 6D force feedback during the insertion stage [84]. The impedance control scheme is widely used in the assembly of charging connectors to achieve active compliant control when positioning is uncertain [85]. Moreover, a hybrid force-position compliant docking method was designed to stabilize the contact force during the charging plug insertion process [86]. The admittance control converts force measurement into position correction instructions, suitable for scenarios where the robot's stiffness is high and the environmental stiffness is unknown. Zeng et al. [87] proposed a biomimetic admittance control strategy, achieving compliant docking of the charging gun and charging interface through position correction. Reinforcement learning does not rely on precise dynamic models of the robotic arm and the environment, but learns through trial and error to continuously optimize the compliant control strategy. Xu et al. [88] used the SAC algorithm based on flexible actor–critic to design an actor–critic framework to achieve the positioning of the charging hole finder.

Table 6. Comparison of compliant control methods.

Control Method	Principle	Algorithms	Advantages	Disadvantages
Passive Compliance [81]	Absorbing the impact force through the institution itself	Elastic floating mechanism Compliant joint	Simple structure Low cost	No active error correction capability
Impedance Control [82–86]	Mass–spring–damper model	Adaptive impedance control Hybrid force-position control	Mature theory Easy parameter tuning	Sensitive to model parameters Low force tracking accuracy
Admittance Control [87]	Convert contact force into position correction commands	Classical admittance control	High accuracy Fast response	Reliance on accurate dynamic models
Reinforcement Learning [88]	Trial-and-error learning	SAC	Manual parameter tuning unnecessary Strong generalization ability	Heavy data requirement

Currently, for the above-mentioned docking scenarios, the main approaches are hybrid force-position control and impedance control. Hybrid force-position control divides the task space into orthogonal subspaces to achieve independent position and force adjustments. In contrast, impedance control uses the dynamic interaction between the contact force and the end effector motion instead of converting the force command into a position tracking target. However, hybrid force-position control requires precise geometric models and a large number of parameter adjustments. Impedance control has difficulty adapting to multi-stage insertion processes when using fixed impedance parameters. In response to the challenges faced by these methods, future research can integrate classical impedance/gain control with reinforcement learning. At the bottom layer, impedance/gain control can be used, and the output of reinforcement learning can be set as small pose corrections, speed corrections, and expected compliant parameter corrections, avoiding the direct output of hard position jumps from reinforcement learning.

4. Challenges and Future Prospects

4.1. The Challenge of High Precision and High Robustness

High precision requires optimal accuracy, necessitating the end effector of the refueling robot to achieve compliant docking with the vehicle's refueling interface. High robustness

pursues generalization capability, demanding that the system can adapt to various application environments. However, the actual refueling environment is a typical unstructured environment, which is characterized by differences in operational objects and uncertainties in operational environments. At present, several commercial prototype models have been developed, but the existing refueling robots can only be compatible with a limited number of vehicle models. The causes of this problem can be attributed to the following three aspects:

(1) The variability of the working environment. In an actual refueling environment, the refueling robot's visual system is subject to various environmental influences, such as lighting, rain, snow, thick fog, and dust. These influences make it difficult for the visual system to cope with different environments, which reduces the system's accuracy and can even cause misidentifications. Any single misidentification could lead to operational interruptions, vehicle damage, and safety accidents.

(2) The variability of the working objects. In an unstructured environment, the shapes, positions, and opening methods of refueling interface vary greatly among different vehicle models. Additionally, vehicle owners have different parking habits, refueling models, and quantities. Therefore, the visual system must have strong generalization capabilities, and the end effector must be able to open and close the various refueling interface. Additionally, the robotic arm must be able to avoid obstacles in real time while moving.

(3) The absence of the refueling interface dataset. For the visual system, it is essential to establish a refueling interface dataset that accounts for variability and differences in the working environment in order to achieve high precision, robust detection and recognition of the refueling interface in various application environments. However, existing datasets have issues such as a limited number of collected images and a single collection scenario. Furthermore, the number of new and modified vehicle releases is increasing rapidly and some models are becoming obsolete. This makes constructing the dataset difficult and requires continuous updates.

The root cause of the challenges in achieving high precision and high robustness for refueling robots lies in our attempt to cope with an infinite and uncertain physical world using a finite and deterministic model. Strategy for accommodating the diversity of vehicle models. On the one hand, offline collection of refueling port images from various vehicle models is required, with collection scenarios including variations in lighting, occlusions, changes in angle, and changes in position. At the same time, physical simulation rendering is employed to generate training samples under various complex working conditions, further enhancing the model's generalization capability. Strategy for consistency in end-to-end annotation. Data annotation guidelines are established, with independent annotation by at least two trained professionals, and cross-validation of annotation results using the same evaluation metrics. Results with ambiguities are referred to experts for adjudication. Strategy for continuous data updates. An open-source community is established, allowing users, manufacturers, and research institutions to upload data. Meanwhile, new model data are regularly collected and, after annotation, the database is periodically updated.

Standardization of refueling interface is difficult to achieve in the short term, as this entails changes in vehicle design and manufacturing, facing significant resistance from automotive manufacturers. Therefore, a stratified and decoupled standardization strategy can be adopted. At the perception layer, models are trained using large-scale labeled datasets to improve generalization capability. At the execution layer, adaptive end effectors are used to address differences in refueling interface. At the decision-making layer, deep reinforcement learning based on real-time force feedback is employed to achieve coordinated control of force and position at the robotic arm's end. This stratified and decoupled strategy avoids

the impracticality of forced unification of refueling interface in the short term and instead achieves hardware compatibility through algorithmic optimization.

In this process, regulatory agencies play a central role, being responsible for coordinating various industries in formulating industry standards for refueling robots and addressing legal gaps in commercial operation. Automotive manufacturers present the greatest obstacle to the standardization of refueling interface, as these interfaces are tied to brand identity and patent deployment. However, by reserving identification marks and opening interface parameters, they can reduce the complexity of recognition and localization. Gas stations can propose compatibility requirements, thereby pressuring upstream enterprises to standardize, and simultaneously drive iterative optimization of robots by collecting operational data. Refueling robot manufacturers should open-source refueling interface datasets to foster community development, while also developing adaptive algorithms to reduce reliance on standardization.

4.2. The Challenges of Safety and Reliability

In terms of safety, the refueling robot system faces the following challenges: (1) Firstly, the functional safety requirements demand that the robot is absolutely safe and reliable in flammable and explosive environments. This means that the mechanical structure and electrical components must meet explosion-proof standards (such as IECEx or ATEX), ensuring that the refueling process does not cause fires or explosions involving oil or gas. (2) Smooth docking of the refueling interface relies on high-precision vision and force-position hybrid control. The docking process must ensure sealing while avoiding structural damage; at the same time, an effective interlock mechanism must be established to prevent vehicles from driving away while armed. (3) The human–machine mixed scenario requires the system to have millisecond-level dynamic obstacle avoidance capabilities. The system can respond to emergencies by integrating real-time data from multiple sensors.

In terms of reliability, the refueling robot system must overcome the severe challenges posed by 24/7 operation. The actuators undergo repeated vibrations and thermal expansion or contraction in extreme environments. The visual sensors may temporarily fail due to changes in lighting conditions, dust obstruction, and so on. Force sensors may experience hardware failures or data drift. The system therefore needs to be able to perform real-time online self-calibration and automatically switch to a safe level or request human intervention when sensors fail or the system drifts. It must also have extremely high stability and strictly prohibit system lag and crashes.

To address the aforementioned problems, future research can be carried out on the following aspects. At the safety level: (1) Research on intelligent interlock mechanisms. During the refueling process, vehicle positions are accurately located based on technologies such as laser and vision. Once unintended vehicle movement is detected, the refueling operation can be stopped immediately, and the connection can be safely and rapidly disconnected. (2) Research on self-sealing refueling nozzles. Miniature and explosion-proof force sensors, flow sensors, temperature sensors, and oil and gas concentration sensors are integrated into the refueling nozzle to monitor contact force, insertion depth, oil flow status, and sealing conditions in real-time during the docking process, thereby preventing fuel leakage. (3) Research on obstacle avoidance algorithms based on behavior prediction. The algorithm can not only detect static and dynamic obstacles, but also analyze the postures and motion trajectories of nearby personnel or objects through algorithms to predict their movement intentions within the next few seconds, thereby achieving active obstacle avoidance instead of passive obstacle avoidance. At the reliability level: (1) Research on deep fusion and cross-validation algorithms for multi-sensors. Instead of relying solely on data from a single sensor, the system enables the fusion and validation of data from

multiple sensors, including vision, LiDAR, force, and others. When the vision sensor fails temporarily, the system can automatically increase the weights of force control and proximity sensing, and even activate virtual sensors for emergency compensation. (2) Research on virtual simulation. A high-precision digital twin model of the refueling robot and its working environment is established, enabling the robot to automatically learn the forces and deformations during the docking process, thereby achieving compliant docking.

4.3. Standardization and Universality Challenges

Since the traditional manual refueling mode can accommodate a wide range of application scenarios, automobile manufacturers lack the incentive to design a unified refueling interface for refueling robots. Although the refueling interfaces of most vehicle models are roughly identical at present, the shapes, positions, and opening mechanisms of the interfaces for some specific models vary significantly, which impairs the design for standardization and universality of refueling robots.

Fuel tank positions are either on the left or right side of the vehicle. The fuel tanks of most vehicle models are located on the right side of the vehicle body, while those of some other models are mounted on the left side. For refueling robots, they cannot obtain the exact position of the fuel tank on the target vehicle and must rely on multi-sensor perception for localization. In particular, range-extended electric vehicles are equipped with fuel doors on both sides of the vehicle body, which further increases the difficulty of perception and recognition. Meanwhile, to accommodate fuel tanks installed at different positions, it is necessary to deploy high-degree-of-freedom long-arm robots or rail-mounted robots on the refueling islands.

The opening mechanisms of fuel door vary considerably. There are four main types of opening mechanisms for fuel door: push-to-open linked to the vehicle's central locking system, mechanical switch-controlled opening from inside the driver's cabin, electrically driven opening via the vehicle-mounted system, and mechanical key-operated opening. However, refueling robots cannot directly operate the mechanical switches inside the vehicle, nor can they send unlocking commands to the vehicle, which necessitates driver assistance via a human–machine interface to complete the refueling operation.

Fuel filler caps are designed in various forms, including screw-on, snap-fit, and capless types. The diversity of fuel filler caps requires the end effector of the robot to be a highly complex "universal gripper", which increases technical complexity and failure rate.

A protracted transition period between new and old vehicle models. Even if new standards are issued now, the billions of non-standardized vehicles already on roads worldwide will still dominate the market over the next decade. refueling robots must be able to service all types of vehicles, which imposes extremely stringent requirements for backward compatibility on their technologies.

To address the aforementioned problems, future research should focus on establishing a unified refueling interface and standard communication protocols between vehicles and robots. First, a unified refueling interface should be developed to fundamentally reduce the technical complexity of refueling robots and cut down the operational costs of enterprises. Second, standard communication protocols should be established, enabling vehicles to actively transmit information such as fuel grade and volume, fuel tank position, and the status of opening and closing mechanisms to robots. Based on the acquired information, robots can conduct visual perception and decision-making control, thereby reducing the degree of manual intervention. Third, targeted training and optimization should be prioritized in closed scenarios with uniform vehicle models and fixed processes, in order to achieve optimal efficiency in controllable scenarios at a limited cost and accumulate the necessary practical experience for the iteration and popularization of the technology.

The above measures represent the only viable path for refueling robots to move from the laboratory to commercial implementation.

4.4. Barriers to Commercial Operation

At the economic level, the current costs of explosion-proof robotic arms, 3D vision sensors, and force sensors are relatively high. For example, Fuelmatics [4] gasoline robots cost $30,000–$40,000 more than traditional fuel pumps. In addition, retrofitting fuel islands, obtaining explosion-proof safety certifications, and the need for equipment maintenance by specialized engineers all prolong the investment payback period, making small- and medium-sized gas stations reluctant to invest.

At the operational level, the color, texture, and opening mechanisms of refueling interfaces currently differ significantly among vehicle brands. Present algorithms struggle to identify the fuel ports of all vehicles, leading to docking failures and thereby reducing refueling efficiency as well as user experience and acceptance. Moreover, mechanical collisions during the robot docking process can cause fuel fires or explosions, for which legal liability gaps exist. In addition, there are no unified industry standards for refueling robots; refueling interface designs, communication protocols, and refueling procedures vary by manufacturer, increasing operational barriers for gas stations.

Although refueling robots currently face economic and operational barriers, in the future, with an aging population, labor costs will continue to rise, and unmanned gas station solutions will have a cost advantage. As future oil, electricity, and hydrogen integrated multi-energy supply models emerge, it will be difficult for humans to manage refueling for multiple energy types, making integrated robotic refueling the development trend.

5. Conclusions

This paper summarizes and analyzes the development history of the refueling robot, including the functions and coupling relationships of each module, the refueling interface and end effector, and the identification and positioning of the refueling port. Research shows that the refueling robot has evolved from an early stage of mechanical positioning to an initial stage of visual perception intelligence. Its system consists of modules such as environmental perception, decision-making control, an actuating mechanism, safety monitoring, and human–machine interaction. The complexity of the end effector is determined by the type of attached interface, which affects the system's reliability and universality. Visual recognition and positioning of refueling interface have evolved from machine learning to deep learning, significantly improving the accuracy and real-time performance of identifying and locating these interfaces. However, in unstructured environments, the diversity of connection interfaces and environmental interference make it difficult for refueling robots to identify all types of refueling interface for vehicles. This limits the robots' large-scale commercial application. Therefore, future research should establish a unified annotation interface standard to reduce the technical complexity of fueling robots. Simultaneously, research should promote the deep integration of refueling robots with artificial intelligence to achieve a leap from software-defined to embodied intelligence and further improve the efficiency and reliability of refueling robots.

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