Proceedings of SEML 2025 Symposium: Machine Learning Theory and Applications
DOI: 10.54254/2755-2721/2025.TJ22276

Intelligent Control Technology and Applications in Smart Robotics

Zhuohao Hu

School of Automation, Chongqing University, Chongqing, China
3013256642@qq.com

Abstract: Intelligent control technologies and intelligent robots represent critical domains in contemporary technological advancement. The rapid development of artificial intelligence (AI) and machine learning has propelled advancements in intelligent control systems, which are now extensively applied in robotics. The application of intelligent robots is becoming increasingly prevalent across industrial, medical, service, and other sectors. Future research will focus on developing more efficient and intelligent control systems, with cutting-edge topics such as human-robot collaboration, autonomous navigation, and multi-sensor fusion emerging as key frontiers. This paper provides a comprehensive review of intelligent control technologies and their applications in intelligent robotics. It aims to enhance researchers' understanding of current advancements and future directions in this field, thereby facilitating further progress in intelligent robotics.

Keywords: Intelligent Control Technology, Intelligent Robots, Deep Learning, Reinforcement Learning

1. Introduction

Robots are products of the era, having evolved through multiple developmental stages and continuously integrated with intelligent technologies. Their applications have expanded across industrial, medical, educational, domestic, and autonomous driving fields, bringing convenience and efficiency to human life. To address challenges such as high nonlinearity and model inaccuracies that are difficult to resolve with traditional control methods, intelligent control has been widely applied in industrial process control and intelligent robot control [1]. Intelligent control systems enable autonomous decision-making, adaptation to environmental changes, and optimization of control objectives. Leveraging artificial intelligence technologies, they achieve autonomous control of complex systems, characterized by their ability to make independent decisions, adapt to dynamic environments, and optimize control performance.

Intelligent control technologies have extensive applications in the field of electrical engineering. As an advanced practice in computer networks, these technologies replace manual management with programmed control, reducing intermediate factors in electrical engineering control systems and simplifying workflows by eliminating redundant steps. They enable operations under diverse conditions, performing rapid data computation and precise adjustments in real time. This not only replaces traditional manual efforts but also delivers superior outcomes. Shuai Zhao et al. [2] summarized the application status of artificial intelligence in power electronics systems, focusing on implementation methods and solutions across design, control, and maintenance phases. For instance,

DOI: 10.54254/2755-2721/2025.TJ22276

in power electronics control, the ant colony optimization algorithm has been applied to maximum power point tracking (MPPT) for photovoltaic systems under partial shading conditions. This approach overcomes limitations of traditional methods, demonstrating advantages such as enhanced system autonomy and precise control. These advancements provide robust theoretical and practical support for intelligent control technologies in electrical engineering.

Simultaneously, intelligent control technologies are increasingly utilized in mechanical manufacturing. With advancements in computer science, intelligent control in mechanical automation is evolving toward the integration of artificial intelligence and automation. The adoption of AI is becoming an inevitable trend to achieve more human-centric production control. Such technologies have already been deployed in production management, particularly in developing intelligent control software systems. Robert K. Katzschmann et al. [3] from ETH Zurich proposed a vision-controlled jetting (VCJ) process for ink deposition, which employs a high-speed 3D vision system to capture printing geometries and enable digital feedback loops for creating complex systems and robots. For example, their tendon-driven hand can sense contact with objects through fingertip pressure, initiate grasping, and halt finger motion based on pressure changes. This exemplifies how intelligent control facilitates interaction between mechanical systems and external environments, offering practical cases for AI-mechatronics integration.

Intelligent control technologies are also widely adopted in robotic control. From a professional perspective, these technologies encompass diverse methodologies. Fuzzy control, for instance, enables robots to make rational decisions in complex and uncertain environments. By translating environmental data and task requirements into fuzzy linguistic variables and establishing corresponding rules, robots can flexibly navigate challenges, such as autonomously planning paths in rugged terrains. Neural network control, inspired by biological neural systems, empowers robots with learning and adaptive capabilities, allowing them to extract patterns from vast datasets and enhance control performance. Jianping Wang et al. [4] developed a vision-based adaptive fuzzy control technique for robotic manipulators, enabling precise operations in complex environments. Their work validated that intelligent control significantly improves adaptability and precision when robots encounter unknown dynamics or challenging environments.

In summary, intelligent control technologies hold substantial potential across multiple domains. This paper aims to analyze the developmental trends of intelligent control technologies and their applications in robotics, evaluate their practical significance, and explore future directions. The insights may inspire researchers in robotics and intelligent control to pursue innovative advancements, fostering further progress in these fields.

2. Development Trends in Intelligent Control Technology

2.1. Integration of Deep Learning and Reinforcement Learning

The combination of deep learning (DL) and reinforcement learning (RL) plays a pivotal role in intelligent control technology. Deep learning extracts features from large datasets through multi-layer neural networks, while reinforcement learning learns optimal policies through interaction with and feedback from the environment. Their integration forms Deep Reinforcement Learning (DRL), significantly enhancing the perception and decision-making capabilities of intelligent robots.

DRL algorithms fully leverage the powerful data representation capabilities of deep learning and the sequential decision-making abilities of reinforcement learning, addressing the complex, nonlinear, and time-varying challenges inherent in optimal decision-making problems in automatic control. DRL algorithms can be categorized into model-based and model-free types. Model-based DRL algorithms select optimal policies based on learned environmental models, including fine-tuning algorithms and intelligent augmentation algorithms. Model-free DRL algorithms, on the other hand,

DOI: 10.54254/2755-2721/2025.TJ22276

derive optimal policies directly through trial-and-error interactions between agents and task environments, primarily including value function-based and policy gradient-based approaches.

As a rapidly developing branch of deep learning, DRL provides solutions for computers to transition from perception to decision-making, enabling intelligent control. Currently, DRL algorithms are gradually being applied in fields such as UAV flight control, mobile robot trajectory control, autonomous vehicle control, and hydraulic servo control [5].

In autonomous navigation, DRL algorithms like Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO) have been applied to path planning and obstacle avoidance for drones and mobile robots. Additionally, researchers have proposed intelligent methods such as Ant Colony Optimization, Particle Swarm Optimization, Simulated Annealing, and Genetic Algorithms to solve global path planning problems, though these methods perform poorly in high-dimensional environments. DRL algorithms enable robots to autonomously plan paths based on environmental states and task changes. For example, even if a pathway is occupied, robots can still find alternative routes to their destinations. Zhou et al. proposed and validated a DQN-based global path planning method, enabling robots to obtain optimal paths in dense environments. The robot's input method directly ingests images, effectively avoiding obstacles. Sui et al. [6] designed a parallel deep DQN algorithm to solve multi-agent constrained formation path planning problems. Wang et al. [7] proposed a mobile robot path planning method based on Double DQN and prioritized experience replay, which plans paths in unknown environments by perceiving local environmental information, with reliability verified through experiments. These studies demonstrate that intelligent path planning enhances the operational capabilities of industrial robots, making it a hot research area in artificial intelligence [8].

In operational tasks, DRL enables robots to perform complex object grasping and manipulation tasks, improving accuracy and efficiency. Multi-robot systems achieve multi-agent reinforcement learning through distributed DRL algorithms, eliminating the need for precise mathematical models of controlled objects, enhancing the ability to process raw sensor data, and reducing the impact of cumulative errors in traditional controller designs. Particularly in addressing multi-robot collaborative challenges, multi-agent reinforcement learning can construct autonomous learning collaborative control strategies under the guidance of joint reward functions, achieving end-to-end mapping from raw multi-information inputs to joint action outputs. In recent years, in dynamic and complex unknown environments, multi-agent reinforcement learning has provided data-driven universal motion control solutions for tasks such as obstacle avoidance, navigation, formation, and task allocation in multi-robot systems [9].

2.2. Internet of Things (IoT) and Edge Computing

The development of the Internet of Things (IoT) and edge computing has provided new opportunities for intelligent control technology. IoT connects various sensors and devices, forming a vast data network that enables intelligent robots to access richer and more real-time environmental information. Edge computing distributes computational tasks to the network edge, reducing data transmission latency and enhancing the system's real-time responsiveness. Edge computing aims to push computational resources closer to the network edge, improving latency and ensuring task execution efficiency. This enables rapid responses to user requests, achieving lower latency and higher bandwidth. Edge computing can shift many controls from centralized clouds to the edge, enabling real-time analysis of massive IoT data. Additionally, edge computing can be applied to smart homes, transmission line monitoring, and smart substations, improving system efficiency and real-time performance. Current research on edge computing focuses on mobile edge networks, fog computing, and edge-cloud integration, with mobile edge computing becoming a key research area [10].

In intelligent robots, IoT technology enables robots to communicate efficiently with other devices in the environment, facilitating collaborative work. For example, industrial robots can interconnect

DOI: 10.54254/2755-2721/2025.TJ22276

with other devices on production lines through IoT, optimizing production processes. Edge computing is particularly important for autonomous navigation and real-time monitoring, as it allows complex computational tasks to be offloaded to edge nodes, enabling robots to make decisions within milliseconds and improving system responsiveness and stability. Due to the large number of nodes involved in IoT data processing at the edge, ensuring high security is challenging. Blockchain strategies can be employed to establish a trusted edge platform, retaining the advantages of edge computing while enabling secure data management through blockchain[11].

2.3. Multi-Sensor Fusion Technology

Multi-sensor fusion technology enhances the environmental perception and decision-making accuracy of intelligent robots by integrating data from multiple sensors. Different sensors have unique strengths and weaknesses, and a single sensor often cannot provide comprehensive and accurate information. Multi-sensor fusion technology integrates data from various sensors using data fusion algorithms, yielding more reliable and comprehensive environmental information. With the continuous advancement of information processing technologies, multi-sensor fusion has been widely applied in fault diagnosis, pattern recognition, remote sensing, and other fields. Weighted fusion methods, which require no prior information and offer high fusion accuracy, have garnered significant attention.

In obstacle avoidance, robots need to detect obstacles from perceptual information, with the key challenge being the determination of spatial location and morphology. The focus of the detection process lies in how to acquire and process obstacle information [12]. For example, multi-sensor fusion technology is applied in wall-climbing robots. By combining multiple sensors, the flexibility of wall-climbing robots can be improved, accurately locating obstacles such as reinforcing ribs and spray pipes on the surfaces of petrochemical storage tanks, preparing the robot for obstacle traversal, enhancing work efficiency, and addressing mobility issues [13].

In complex environments, multi-sensor fusion technology enables precise autonomous navigation and localization for robots. Simultaneous Localization and Mapping (SLAM) is a typical application. In unmanned ship docking, frequent operations, dynamic obstacles, and harsh weather pose significant challenges. SLAM technology can largely address these issues. In port environments, multi-sensor fusion compensates for the interference caused by open spaces, limited available information, and wind and wave disturbances on SLAM algorithms. SLAM algorithms estimate ship position, velocity, and direction using multi-sensor data, constructing maps and enabling real-time localization in port environments. The high-precision point cloud maps generated provide environmental information for autonomous ship navigation and serve as references for subsequent path planning algorithms [14]. Furthermore, multi-sensor fusion technology shows broad application prospects in industrial robots, medical robots, and service robots [15].

2.4. Human-Robot Collaborative Intelligence

Human-robot collaborative intelligence is a key direction in the development of intelligent control technology. It emphasizes collaboration and integration between robots and humans, aiming to enhance the naturalness and intelligence of human-robot interaction. This enables robots to better understand and respond to human needs. Through affective computing and cognitive computing technologies, robots can perceive and understand human emotions and intentions, providing more personalized and intelligent services.

In the industrial sector, human-robot collaborative intelligence enables robots to work alongside human workers, improving production efficiency and safety. Wearable robotic limbs, distinct from prosthetics and exoskeletons, offer large workspaces and flexible movements, enabling load-bearing

DOI: 10.54254/2755-2721/2025.TJ22276

and precise tasks. When wearers perform tasks in hazardous environments or maintain uncomfortable postures, these robotic limbs can support the human body by bracing against walls, grabbing railings, or anchoring to the ground, ensuring safe, comfortable, and stable task completion [16]. In the medical field, assistive rehabilitation robots and surgical robots leverage human-robot collaborative intelligence to provide personalized patient care and precise surgical operations. Assistive robots are designed to help individuals with mobility impairments perform daily activities such as eating, washing, and using the toilet. In neurosurgery, robots are primarily used for precise spatial localization of brain lesions and assisting doctors in holding and stabilizing surgical instruments. These robots are guided by pre-operative medical imaging for navigation and positioning [17].

3. Applications of Intelligent Control Technology in Intelligent Robots

3.1. Autonomous Navigation

Autonomous navigation is one of the most fundamental and critical functions of intelligent robots, involving path planning, environmental perception, localization and mapping, obstacle detection, and avoidance.

(1) Path Planning: Intelligent control technology utilizes various algorithms, such as Dijkstra's algorithm and Rapidly-exploring Random Trees (RRT), to achieve path planning. In recent years, Deep Reinforcement Learning (DRL) has been increasingly applied in path planning, enabling robots to handle more complex and dynamic environments. For example, path planning algorithms based on Deep Q-Networks (DQN) can learn optimal policies to achieve efficient navigation for robots in unknown environments.

(2) Environmental Perception and Mapping (SLAM Technology) **: Simultaneous Localization and Mapping (SLAM) is a crucial tool for autonomous navigation. SLAM technology integrates data from multiple sensors, such as LiDAR, cameras, and Inertial Measurement Units (IMUs), to achieve real-time mapping and precise localization. For instance, lunar rovers operate over long durations and large areas, making localization essential for their tasks. Applying SLAM technology to lunar rovers can significantly enhance their operational efficiency [18]. Intelligent control technology in SLAM enables robots to self-localize and navigate in dynamic environments, as seen in advanced algorithms like ORB-SLAM and Cartographer. For example, in the semi-open and complex environment of a cattle farm, robots use Dijkstra's algorithm for navigation and the Adaptive Monte Carlo Localization (AMCL) algorithm to fuse LiDAR and IMU data for localization. This approach addresses errors caused by wheel slippage during hay-pushing tasks, enabling precise navigation and successful completion of tasks in complex farm environments [19].

(3) Obstacle Detection and Avoidance: Intelligent control technology leverages sensor data for obstacle detection and avoidance, using LiDAR, ultrasonic sensors, and cameras to perceive the surrounding environment in real time. LiDAR, which emits laser beams to detect target positions and velocities, can create high-precision 3D environmental maps. It is a critical sensor in autonomous driving systems, capable of distinguishing between posters and moving pedestrians, modeling 3D spaces, detecting static objects, and accurately measuring target motion speeds [20]. Brain-controlled wheelchairs, a new type of intelligent wheelchair controlled by user EEG signals, utilize sensors to perceive the external environment and alert users to the direction and distance of obstacles, enhancing safety and reliability [21]. Traditional Artificial Potential Field (APF) algorithms abstract robots as points influenced by a potential field composed of an attractive field centered on the target and a repulsive field centered on obstacles [22]. Applying APF to drones improves their autonomous obstacle avoidance capabilities, enhancing their mobility and flexibility [23].

DOI: 10.54254/2755-2721/2025.TJ22276

3.2. Human-Robot Interaction

Human-robot interaction is a vital means for intelligent robots to communicate and collaborate with human users, involving speech recognition, gesture recognition, and affective computing.

(1) Speech Recognition and Processing: Speech recognition technology, powered by intelligent control algorithms, enables robots to accurately recognize and respond to human voice commands. Natural Language Processing (NLP) combined with deep learning algorithms allows robots to understand and execute complex voice commands, improving the efficiency and naturalness of human-robot interaction. For example, speech recognition systems based on Recurrent Neural Networks (RNNs) and Transformers are widely used in service robots and home assistants.

(2) Gesture Recognition and Motion Understanding: Gesture recognition, enabled by computer vision and deep learning algorithms, allows robots to interpret and respond to human gestures and actions. Convolutional Neural Networks (CNNs) have been applied to gesture recognition, enabling robots to accurately identify and interpret various gesture commands, enhancing the intuitiveness and convenience of human-robot interaction. For instance [24], a study used electronic skin to collect pressure data from different subjects under various conditions and developed a Factorized Spatio-Temporal Convolutional Neural Network ((2+1)D CNN) model for tactile gesture classification. This model effectively extracts spatio-temporal features of tactile gestures, achieving high recognition accuracy and strong generalization capabilities. It also establishes a connection between tactile gestures and emotions, laying a data foundation for tactile recognition in human-robot interaction.

(3) Emotion Recognition and Affective Computing: Affective computing enables robots to recognize user emotions through multimodal information such as voice, facial expressions, and behavior, and respond accordingly. Intelligent control algorithms based on affective computing help social and companion robots provide more personalized and humanized services, improving user experience and satisfaction. For example, a study [25] proposed an interactive robot system for assisting autism rehabilitation, enabling the robot to exhibit emotional cognition, emotional transfer, and feedback during interactions. This system, grounded in affective computing, integrates human-robot interaction into autism rehabilitation training, reducing costs while significantly improving rehabilitation outcomes.

3.3. Task Execution and Coordination

Intelligent robots demonstrate strong capabilities in task execution and coordination, particularly in multi-robot systems, where collaborative work enhances overall efficiency and task completion quality.

(1) Collaborative Control in Multi-Robot Systems: Multi-robot systems use intelligent control algorithms to achieve collaborative work and resource sharing among multiple agents. For example, distributed reinforcement learning algorithms and game theory methods enable multiple robots to efficiently collaborate in complex task environments, such as search and rescue or environmental monitoring. A study [26] proposed a frontier-based multi-robot collaborative exploration method, which identifies boundaries between known and unknown areas and assigns robots to explore these boundaries. This method is highly effective for multi-robot exploration of new areas while avoiding redundant exploration.

(2) Task Allocation and Scheduling Algorithms: Task allocation and scheduling are critical issues in multi-robot systems. Intelligent control technology employs optimization algorithms, such as Ant Colony Optimization (ACO), Genetic Algorithms (GA), and Particle Swarm Optimization (PSO), to dynamically allocate tasks and ensure efficient coordination among robots. ACO, for instance, is used to find optimal paths in graphs and solve combinatorial optimization problems. A study [27] designed an adaptive task scheduling algorithm for cloud computing based on ACO, incorporating a

DOI: 10.54254/2755-2721/2025.TJ22276

pheromone adaptive update mechanism to improve convergence speed and generate task distribution plans with shorter execution times, lower costs, and balanced load rates. This algorithm performs better in solving large-scale task scheduling problems.

(3) Real-Time Control and Response: Intelligent control technology enables robots to quickly adapt to environmental changes and make real-time decisions and actions. Real-time control systems, combined with fuzzy control, adaptive control, and predictive control, ensure efficient operation and task execution in dynamic environments. To meet the high-precision requirements of industrial robots, a study [28] investigated real-time trajectory error compensation methods using laser trackers to measure end-effector positions. This method, based on Continuous Dynamic Time Warping (CDTW), calculates position errors at each moment of the robot's trajectory. Additionally, a PID parameter tuning technique based on gray relational analysis and response surface methodology was developed to achieve real-time compensation.

4. Conclusion

Intelligent control technology and intelligent robots are pivotal areas in the development of modern science and technology, driving innovation and efficiency improvements across multiple industries. Based on the analysis of the current research status of intelligent control technology and its applications in intelligent robots, the following conclusions can be drawn:

1. Diverse Applications of Intelligent Control Technology

The application of intelligent control technology in intelligent robots demonstrates its diversity, including methods such as adaptive control, fuzzy control, and neural network control. These technologies effectively address the limitations of traditional control methods in complex environments, enhancing the adaptability of robots in dynamic and uncertain settings.

2. Integration of Deep Learning and Reinforcement Learning

The combination of deep learning and reinforcement learning has significantly improved the perception and decision-making capabilities of intelligent robots. Through this integration, robots can autonomously navigate and perform tasks in dynamic and complex environments, demonstrating higher efficiency and accuracy, thereby expanding their application scenarios.

3. Synergistic Role of IoT and Edge Computing

The integration of the Internet of Things (IoT) and edge computing provides intelligent control technology with real-time data processing and response capabilities. This synergy enhances the environmental perception and collaborative capabilities of intelligent robots, driving advancements in smart manufacturing, smart homes, and other fields, while laying the foundation for the real-time performance and reliability of future intelligent systems.

4. Development of Human-Robot Collaborative Intelligence

The advancement of human-robot collaborative intelligence enables robots to better understand and respond to human needs, improving the naturalness and intelligence of human-robot interaction. In the future, this technology will play a greater role in industrial, medical, and service fields, further deepening and broadening human-robot collaboration.

The research presented in this paper not only provides valuable references for academic studies but also offers theoretical support and practical guidance for technological upgrades and product innovation in the industrial sector. With the continuous progress of intelligent control technology and intelligent robotics, breakthroughs are expected in more fields in the future.

References

[1] Biao, S., Ying, L., Zhao-Jun, X., & Li-Jie, W. Research on the Intelligent Numerical Control Machine for Wood Processing. 2010 International Conference on E-Product E-Service and E-Entertainment,

[2] Zhao, S., Blaabjerg, F., & Wang, H. (2020). An overview of artificial intelligence applications for power electronics.

DOI: 10.54254/2755-2721/2025.TJ22276

[3] Khatib, O. (1987). A unified approach for motion and force control of robot manipulators: The operational space formulation. IEEE Journal on Robotics and Automation, 3(1), 43-53.

[4] Shieh, N. C., Chang, C. T., Lin, C. L., & Jan, H. Y. (2002). Robust position control of a transportation carriage directly driven by linear motor using wavelet neural. Engineering Applications of Artificial Intelligence, 15(5), 479-489.

[5] Ma, C., Li, A., Du, Y., Dong, H., & Yang, Y. Efficient and scalable reinforcement learning for large-scale network control. Nature Machine Intelligence.

[6] Oda, T., Obukata, R., Ikeda, M., Barolli, L., & Takizawa, M. (2017). Design and Implementation of a Simulation System Based on Deep Q-Network for Mobile Actor Node Control in Wireless Sensor and Actor Networks. 2017 31st International Conference on Advanced Information Networking and Applications Workshops (WAINA),

[7] Sui, Z., Pu, Z., Yi, J., & Tan, X. (2018). Path Planning of Multiagent Constrained Formation through Deep Reinforcement Learning. IEEE.

[8] Wang, Y., Fang, Y., Lou, P., Yan, J., & Liu, N. (2020). Deep Reinforcement Learning based Path Planning for Mobile Robot in Unknown Environment. Journal of Physics Conference Series, 1576, 012009.

[9] Li, C., Zheng, P., Yin, Y., Wang, B., & Wang, L. (2023). Deep reinforcement learning in smart manufacturing: A review and prospects. CIRP Journal of Manufacturing Science and Technology.

[10] Wang, D., Deng, H., & Pan, Z. (2020). MRCDRL: Multi-Robot Coordination with Deep Reinforcement Learning. Neurocomputing, 406(1).

[11] Hua, L., Junguo, Z., & Fantao, L. (2013). Internet of Things Technology and its Applications in Smart Grid. Telkomnika Indonesian Journal of Electrical Engineering, 12(2), 940-946.

[12] Nyamtiga, Sicato, Rathore, Sung, & Park. (2019). Blockchain-Based Secure Storage Management with Edge Computing for IoT. Electronics, 8(8), 828.

[13] Meichen, L., Jun, C., Xiang, Z., Lu, W., & Yongpeng, T. (2018). Dynamic obstacle detection based on multi-sensor information fusion. IFAC-PapersOnLine, 51(17), 861-865.

[14] Xue, J., Chen, J., Stancu, A., Wang, X., & Li, J. (2023). Spatial Trajectory Tracking of Wall-Climbing Robot on Cylindrical Tank Surface Using Backstepping Sliding-Mode Control. Micromachines, 14(3), 20.

[15] Wang, Z., Klingner, A., Magdanz, V., Misra, S., & Khalil, I. S. M. (2024). Soft Bio‐Microrobots: Toward Biomedical Applications. Advanced Intelligent Systems (2640-4567), 6(2).

[16] Divekar, N. V., Thomas, G. C., Yerva, A. R., Frame, H. B., & Gregg, R. D. (2024). A versatile knee exoskeleton mitigates quadriceps fatigue in lifting, lowering, and carrying tasks. Science Robotics, 9(94), Article eadr8282.

[17] Kyrarini, M., Lygerakis, F., Rajavenkatanarayanan, A., Sevastopoulos, C., & Makedon, F. (2021). A Survey of Robots in Healthcare.

[18] Yiqiao, Wang, Wei, Zhang, Pei, & An. (2017). A Survey of Simultaneous Localization and Mapping on Unstructured Lunar Complex Environment. AIP Conference Proceedings, 1890(1), 1-9.

[19] Abanay, A., Masmoudi, L., Ansari, M. E., Gonzalez-Jimenez, J., & Moreno, F. A. (2022). LIDAR-based autonomous navigation method for an agricultural mobile robot in strawberry greenhouse: AgriEco Robot. AIMS Electronics and Electrical Engineering.

[20] Li, B., Lin, Q., & Li, M. (2023). Frequency-angular resolving LiDAR using chip-scale acousto-optic beam steering. Nature.

[21] Odetti, L., & Sabatini, A. M. (1996). A navigation system for advanced wheelchairs using sonar and infrared sensors. International symposium on robotics and manufacturing,

[22] Siming, W., Tiantian, Z., & Weijie, L. (2018). Mobile Robot Path Planning Based on Improved Artificial Potential Field Method. IEEE, 29-33.

[23] Khatib, O. (1987). A unified approach for motion and force control of robot manipulators: The operational space formulation. IEEE Journal on Robotics and Automation, 3(1), 43-53.

[24] Nicholls, H. R., & Lee, M. H. (1989). A Survey of Robot Tactile Sensing Technology. International Journal of Robotics Research, 8(3), 3-30.

[25] Silva, P. D., Tadano, K., Saito, A., Lambacher, S. G., & Higashi, M. (2009). The development of an assistive robot for improving the joint attention of autistic children. IEEE International Conference on Rehabilitation Robotics,

[26] Yan, X., Zeng, Z., He, K., & Hong, H. (2023). Multi-robot cooperative autonomous exploration via task allocation in terrestrial environments. Frontiers in Neurorobotics.

[27] Liu, H. (2022). Research on Cloud Computing Adaptive Task Scheduling Based on Ant Colony Algorithm. Optik.

[28] Li, R., Ding, N., Zhao, Y., & Liu, H. (2023). Real-time trajectory position error compensation technology of industrial robot. Measurement, 208, 112418-.