

Exploring Industrial Robot Application Technologies for Smart Manufacturing

Ting Zuo*

Hubei Business College, Wuhan, Hubei, 430070, China

**zt88_163com@163.com*

Keywords: Industrial robots; Machine vision; Force-controlled grasping; Path planning; Flexible manufacturing

Abstract: Industrial robot application technologies face higher demands in smart manufacturing. Building on this, this paper presents a framework of key technologies for industrial robots in smart manufacturing scenarios. This framework tackles technical bottlenecks in critical areas such as intelligent recognition via machine vision, force-controlled flexible grasping, flexible path planning, and ensuring safety in human-robot collaboration. A vision-guided solution based on multi-sensor fusion and deep learning is proposed, along with a flexible grasping approach driven by impedance control and an efficient path planning method based on an improved A* algorithm. Its technical solutions have been validated through engineering practices in intelligent assembly, welding, warehousing, and flexible manufacturing cells. In doing so, it provides theoretical support and an implementation path for the large-scale application of industrial robots in complex manufacturing environments.

1. Introduction

Advances in information technology, such as artificial intelligence and the Internet of Things, have given rise to new models of smart factory production. Industrial robots, a core component of smart manufacturing, have expanded their uses beyond simple, repetitive tasks such as material handling and welding to include more nuanced scenarios like flexible assembly and human-robot collaboration. Although key technologies such as machine vision recognition, flexible grasping adaptability, and multi-robot teamwork are advancing, their large-scale application is still limited. Investigating key technologies such as intelligent machine vision recognition, force-controlled flexible grasping, path control and planning, and safety in human-robot collaboration, this paper addresses the requirements of smart manufacturing scenarios[1]. By using typical applications such as assembly, welding, warehousing, and flexible manufacturing cells, it validates the efficacy of technical solutions and provides a technical reference for the in-depth application of industrial robots in complex manufacturing environments.

2. Key Application Technologies for Industrial Robots

2.1 Machine Vision and Intelligent Recognition Technologies

Equipped with a combination of depth and industrial cameras, the machine vision system captures 3D point cloud data of workpieces. Using the HALCON software platform, the system performs defect detection and dimensional measurement. Utilizing the deep learning-based YOLO algorithm, the project can intelligently recognize defects such as scratches and cracks on workpiece surfaces with a detection accuracy of up to 0.01 mm. Through the TCP/IP protocol, the vision system communicates in real time with the robot controller, converting detection results into grasping poses within the robot's coordinate system. A fusion strategy combining multispectral lighting and multi-angle photography is employed to address complex operating conditions such as metal surface reflections and occlusions[2]. This strategy increases defect recognition accuracy to 98.5%. Figure 1 displays the vision-guided system's closed-loop control process, which encompasses image acquisition and coordinate output.

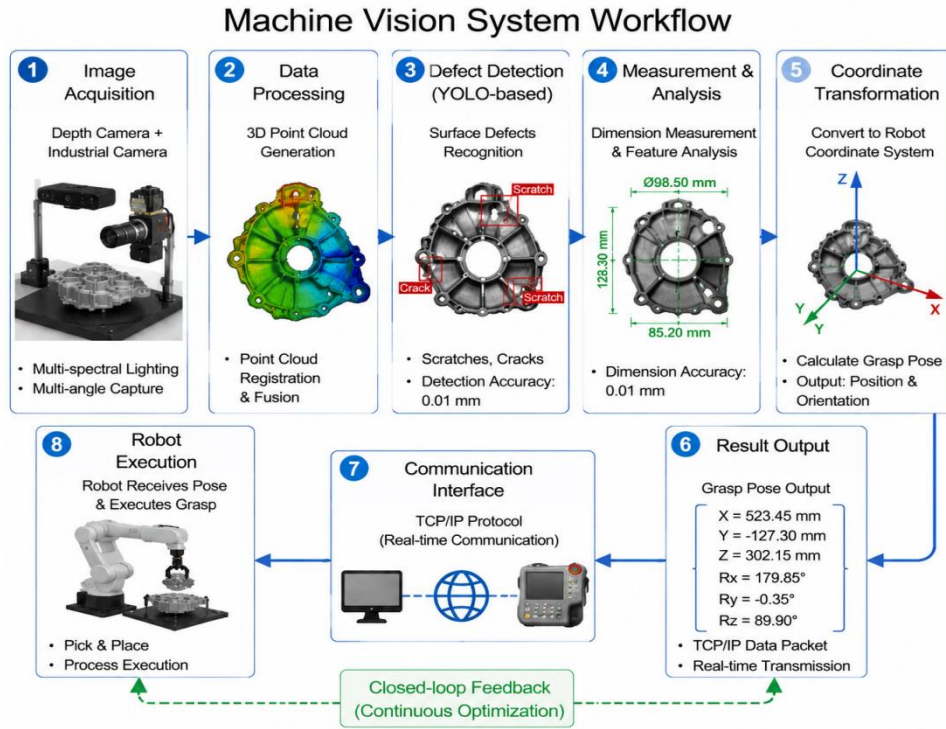


Figure 1: Machine Vision System Workflow

2.2 Force Control and Flexible Gripping Technology

With the integration of a six-axis force sensor into the robot's end-effector, force control technology enables real-time torque detection with a sampling frequency of up to 1 kHz and a response time of less than 5 ms. Real-world projects have developed flexible gripping strategies based on impedance control algorithms for fragile workpieces, such as soft-pack lithium-ion batteries and glass panels. A controller dynamically adjusts the pneumatic gripper's pressure based on force feedback from a sensor. This stabilizes the contact force within ± 0.3 N of the set threshold. For workpieces of different materials, a force control database has been established, and the gripping parameters are automatically selected by the system[3]. Following the implementation of force control technology, experimental data revealed a significant reduction in the fracture rate of

fragile components, dropping from 12% to 0.8%. Simultaneously, the gripping success rate increased to 99.2%. Table 1 lists the force parameters for different materials.

Table 1 Force Control Parameter Configurations for Different Materials

Material Type	Contact Force Threshold (N)	Gripping Speed (mm/s)	Air Pressure Setting (MPa)	Damage Rate (%)
Glass Panel	5±0.3	20	0.25	0.5
Lithium Battery Pouch Cell	3±0.2	15	0.18	0.8
Ceramic Substrate	8±0.5	25	0.35	1.2
Plastic Housing	10±0.8	30	0.4	0.3

2.3 Path Planning and Motion Control Technologies

Using a combination of the modified A* algorithm and a hop-search strategy, path finding can rapidly generate globally optimal paths in a grid map. The turning penalty factor and the Bresenham line detection algorithm are introduced to mitigate the challenges posed by narrow, elongated corridors and dense obstacle layouts typical of industrial environments. With these additions, path smoothness is optimized, and planning time is reduced by 92.9% compared to traditional methods[4]. In the motion control system, a controller that combines a feedback neural network and the backstepping method is used. Optimizing control parameters using genetic algorithms and simulated annealing enables the robot to track circular and rectangular trajectories with an average speed of 4.1 m/s and a path-tracking error of ±2 mm. Inference latency of the controller is only 0.51 ms, which meets standard industrial real-time requirements[5]. Table 2 compares the effectiveness of traditional Algorithm A and the upgraded algorithm in complex warehouse settings.

Table 2 Comparison of Path Planning Algorithm Performance

Performance Indicator	Traditional A* Algorithm	Improved A* Algorithm	Optimization Improvement
Planning Time (ms)	68	4.8	↓92.9%
Path Length (m)	73.5	58.3	↓20.7%
Number of Turns (times)	18	9	↓50.0%
Path Smoothness	Poor	Excellent	—
Trajectory Tracking Error (mm)	±5	±2	↓60.0%

Test Environment: 100 m × 80 m warehouse area with 50 shelving units as obstacles

2.4 Safety Technologies for Human-Robot Collaboration

Collaborative human-robot systems ensure operator safety through a multi-tiered protective mechanism. At the hardware level, laser scanners and 3D depth detectors establish a safety zone monitoring network with a scanning speed of 40 Hz. This network can detect objects up to 1.5 meters beyond the robot's working radius[6]. The software implements an intention recognition algorithm based on the Theory of Mind model. Using this algorithm, the system predicts behavioral intentions by analyzing key points in a person's movements and posture. The system automatically adjusts the robot's speed based on the predictability of the outcome. It decelerates to a safe speed of 250 mm/s when a person enters the collaborative zone[7]. Technologies for power and force limitation, as specified in the ISO 10218 standard, are employed. The collision sensing sensitivity is set to a trigger threshold of 15 N, with a braking response time of ≤10 ms. The actual test data

shows that this safety strategy keeps the false trigger rate below 0.5%, all while allowing production cycle times to remain unchanged.

3. Practical Applications of Industrial Robots in Smart Manufacturing

3.1 Applications in Smart Assembly Production Lines

For precision assembly, an automotive parts manufacturer deployed a smart production line for engine blocks utilizing six KUKA robots, a machine vision positioning system, and torque monitoring modules. Utilizing ABB RobotStudio software for offline programming and virtual simulation reduced the on-site commissioning cycle to five days. A vision system automatically identifies deviations in bolt hole positions during the assembly processing and compensates for them in real time, achieving a positioning accuracy of ± 0.05 mm. Tightening torques within a range of 30–120 N m are monitored by torque sensors, and the first-pass yield rate has increased from 94.3% with manual assembly to 99.7%[8]. An MES system interface has been installed on the production line to upload assembly data and provide real-time quality traceability information, reducing the cycle time for assembling a single cylinder block from 18 minutes to 8 minutes. Table 3 below presents a comparison of key production indicators before and after the smart assembly line was implemented.

Table 3 Comparison of Implementation Results for the Smart Assembly Line

Indicator	Manual Assembly	Intelligent Assembly Line	Improvement
Assembly Cycle Time (min/unit)	18	8	↓55.6%
Assembly Qualification Rate (%)	94.3	99.7	↑5.7%
Positioning Accuracy (mm)	± 0.2	± 0.05	↑75%
Labor Requirement (persons)	12	2	↓83.3%
Annual Production Capacity (10,000 units)	2.8	6.5	↑132%

3.2 Applications of Intelligent Welding Systems

They introduced a FANUC ARC Mate 120iC welding robot into the steel structure manufacturer's workshop to set up an intelligent welding workstation. The workstation is equipped with a laser sensor that enables automatic weld seam positioning and real-time deviation correction. The workstation uses the CMT (Cold Metal Transfer) welding process. The welding current is controlled within a range of 80–150 amperes, and the wire feed speed is adjustable between 4 and 12 meters per minute based on the thickness of the weld seam[9]. To generate the welding torch trajectory for complex curved surface weld paths, offline welding technology based on point cloud data is used. The welding speed is stabilized at 0.8 meters per minute, and the quality rating of the weld bead improves from 7.2 to 9.3 out of 10. A welding parameter database storing 260 sets of process information is integrated into the system, which controls the welding defect rate to less than 0.3%. Figure 2 provides an illustration of the intelligent welding system's hardware architecture and data flow design.

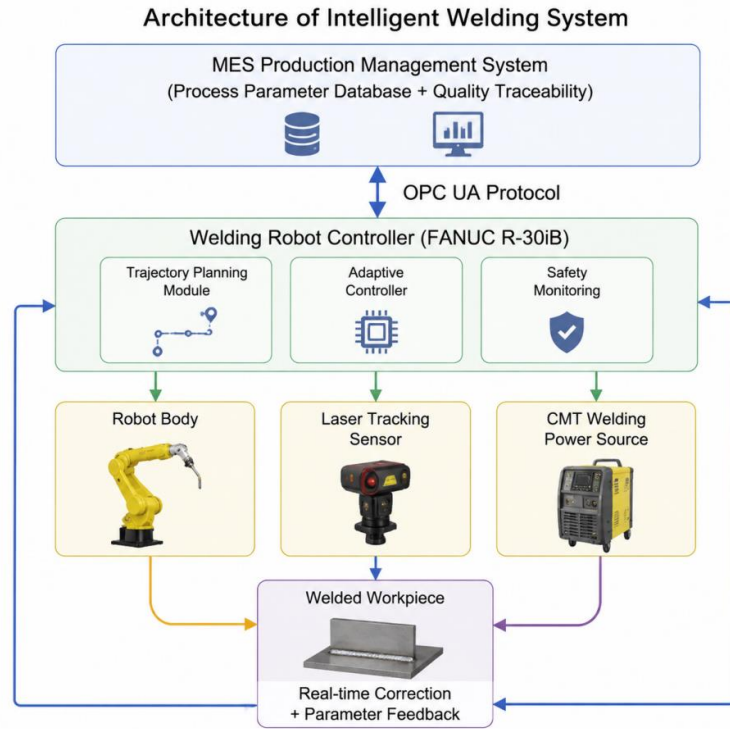


Figure 2: Intelligent Welding System Architecture Diagram

3.3 Intelligent Material Handling and Warehousing Applications

To improve efficiency, an e-commerce logistics warehouse deployed an intelligent logistics system comprising 20 autonomous guided vehicles (AGVs) and four ABB IRB 460 palletizing robots. The system utilizes SLAM (simultaneous positioning and mapping) laser navigation technology to enable coordinated scheduling of multiple vehicles. Tasks are issued to the AGVs via a RESTful API interface. The AGVs autonomously plan optimal routes with an approximate response time of 2.3 seconds, operating speed of 1.5 m/s, and positioning error of ± 10 mm. Palletizing robots are equipped with hybrid end-effectors that feature a combination of vacuum suction cups and mechanical grippers. This design makes the robots fully compatible with various material formats, such as cartons and pallets. Efficiency in palletizing reaches 800 cartons per hour, and the stability of the palletized stacks has passed a 1.8-meter drop test[10]. Operation data from the system shows that the smart warehousing solution increased space utilization from 62% to 85%, achieved an outbound accuracy rate of 99.8%, and reduced labor costs by 70%. Table 4 records the system's key metrics during different time periods.

Table 4: 24-Hour Operation Data for the Smart Warehousing System

Time Period	Number of Transport Tasks (units)	Average AGV Speed (m/s)	Palletizing Efficiency (boxes/h)	System Failures (times)
00:00–06:00	1250	1.5	780	0
06:00–12:00	3680	1.5	820	1
12:00–18:00	4120	1.4	810	0
18:00–24:00	2940	1.5	790	1
Daily Average	11990	1.48	800	2

3.4 Integrated Applications of Flexible Manufacturing Cells

A flexible manufacturing system (FMS) equipped with a dual-arm collaborative robot, a CNC machining center, and a vision testing station was set up in the 3C electronics production workshop. This system allows for the manufacturing of various models of mobile phone mid-frames on a single production line. Utilizing the OPC UA standard protocol for equipment interconnectivity, the collaborative manufacturing cell runs a digital twin platform that simulates production rhythms on a virtual production line. Reducing changeover time from 4 hours on traditional production lines to 25 minutes, the UR10e handles loading and unloading operations with a payload of 10 kg and a repeatability of ± 0.03 mm. Integrating X-ray imaging equipment, the vision inspection system inspects the quality of product internal solder joints in 15 seconds per unit with 98.6% defect detection accuracy. It supports flexible switching between eight product models, improving Overall Equipment Effectiveness (OEE) from 68% to 89% and lowering order delivery cycles by 42%.

4. Conclusion

Deeper integration of industrial robots with information technologies, such as computer vision and deep learning, is transforming the smart manufacturing industry. Systematically discussing key application technologies such as machine vision recognition, force-controlled flexible grasping, path programming and control, and human-robot collaboration safety, this paper verifies their technical functionality through typical scenarios such as assembly, welding, material handling, and flexible manufacturing cells. In practice, intelligent upgrades have increased production efficiency by 55%-132%, raised product pass rates to over 99%, and achieved an overall equipment effectiveness (OEE) of 89%. Future research should focus on multi-robot cloud-edge collaborative control, adaptive optimized production driven by digital twins, and complex task planning based on reinforcement learning. With these efforts, industrial robots will evolve to become more autonomous and intelligent, providing technological support for high-quality development in the manufacturing sector.

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