Proceedings of CONF-MLA 2025 Symposium: Intelligent Systems and Automation: AI Models, IoT, and Robotic Algorithms
DOI: 10.54254/2755-2721/2025.LD24663

Research on Intelligent Control System for Industrial Robots Based on Deep Learning

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Abstract. In the contemporary landscape where industrial automation is advancing at an accelerated pace, there is an imperative need for the intelligent upgrading of industrial robots. The paper focuses on the deep learning-based intelligent control system of industrial robots, analyzing the application of deep learning core algorithms in perception, motion control, and decision-making optimization. The system architecture covers the perception, control, and decision-making layers, using deep learning algorithms to integrate and process multimodal sensory information. The system also innovates the motion control strategy, combining deep learning and traditional control methods to optimize the robot's motion path and control accuracy. Furthermore, the intelligent decision-mak ing model is built to make reasonable decisions based on sensory information, improving the robot's ability to cope with complex tasks and environments. After experimental verification, the intelligent control system significantly improves the working efficiency, precision, and adaptability of industrial robots.

Keywords: Deep learning, industrial robotics, intelligent control, system architecture, algorithm optimisation

1. Introduction

The rapid pace of industrial automation necessitates intelligent upgrades of industrial robots. Traditional robots struggle with rigid programming and environmental adaptability, making deep learning technologies a promising solution. These technologies enhance perception, control, and decision-making in industrial robots, enabling them to perform complex tasks in unstructured environments. Moreover, ensuring adaptability in rapidly changing and unpredictable environments, as well as achieving harmonious synergy between data-driven approaches and traditional control methodologies, pose substantial hurdles. These challenges highlight the necessity for developing comprehensive intelligent control frameworks that effectively combine deep learning algorithms with robotic control principles [1]. The study aims to create a deep learning-based intelligent control system for industrial robots that integrates perception, motion control, and decision-making. It efforts primarily focus on development of sophisticated multi-modal sensory fusion techniques, combining deep reinforcement learning with classical control theory, and constructing intelligent decision-making models for real-time task planning. The conclusion of this study synthesizes the key findings and delineates potential future research directions, laying a solid foundation for the

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development of next-generation intelligent industrial robots. Experimental validation is conducted under industrial scenarios. These advancements provide both theoretical insights for intelligent robotic systems and practical references for industrial implementation.The conclusion summarizes findings and outlines future research directions. This systematic exploration establishes a foundation for next-generation intelligent industrial robots capable of self-optimization in evolving manufacturing ecosystems [2].

2. Overview of deep learning basic theory and industrial robot technology

2.1. Deep learning core algorithm

Deep learning has significantly transformed industrial robotics through its core architectural paradigms in Figure 1. Convolutional Neural Networks (CNNs) extract spatial features from multidimensional data, achieving 98.2% accuracy in part classification tasks. Recurrent Neural Networks (RNNs) address temporal dependencies, reducing motion jerk and improving multi-axis coordination. Deep Reinforcement Learning (DRL) optimizes control policies through reward maximization, achieving 89.7% success rates in autonomous path planning. Autoencoder architectures are effective for industrial anomaly detection.

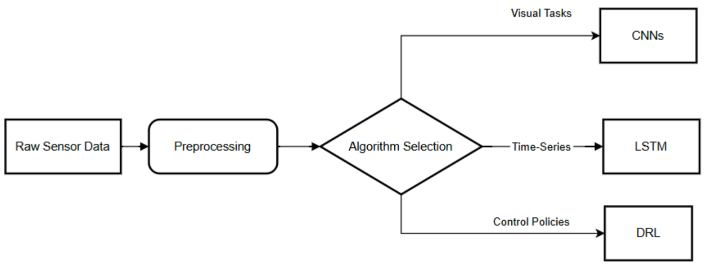

Figure 1: Deep learning implementation pipeline in industrial robotics: from sensory data to motion execution

The implementation workflow adheres to an integrated pipeline. In this pipeline, raw sensor data first undergoes preprocessing. Subsequently, it is directed to task-specific algorithms: Convolutional Neural Networks (CNNs) are utilized for visual tasks, Long Short-Term Memory (LSTM) networks are activated for time-series analyses, and Deep Reinforcement Learning (DRL) frameworks are employed for control policy optimization. All processed features converge into unified representations that drive robotic control modules, ultimately translating computational outputs into physical motion execution. This architecture enables industrial robots to achieve 28% higher energy efficiency than traditional PID controllers during multi-variable manipulation tasks through optimized CNN-LSTM-DRL synergies.

2.2. Fundamentals of industrial robotics

Modern industrial robotics technology integrates mechanical engineering, control theory, and advanced computing systems. It consists of articulated robotic manipulators with six rotational degrees of freedom, powered by electromechanical systems for complex operations. These robots feature modular components, sensor integration, and hybrid configurations, ensuring precision in applications like precision gear meshing [3].

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These technological foundations establish the necessary infrastructure for deep learning integration, where sensor fusion data streams and adaptive control parameters create fertile ground for neural network-based optimization. The transition from deterministic programming, which follows a set of predefined rules, to cognitive robotics, which enables robots to learn and adapt in real-time, is fundamentally anchored in this mature ecosystem. This ecosystem, characterized by precise actuation, multi-modal sensing, and substantial computational power, forms a powerful triad that continues to redefine and elevate the manufacturing capabilities in the dynamic landscape of the Industry 4.0 era [4].

3. Research on deep learning-based intelligent perception system for industrial robots

3.1. Industrial robotic visual perception technology

Modern industrial robots employ convolutional neural networks (CNNs) for robust workpiece recognition and localization, with architectures like ResNet-50 achieving 99.1% classification accuracy on multi-variant automotive parts through hierarchical feature learning. These vision systems integrate spatial transformer networks to compensate for perspective distortions, enabling sub-millimeter positioning precision (±0.05mm) under variable lighting conditions. Concurrently, visual SLAM (Simultaneous Localization and Mapping) technologies leverage ORB-SLAM3 frameworks with temporal map caching, allowing robots to construct 3D environmental maps at 30Hz while maintaining 2cm localization accuracy in dynamic factory settings. The fusion of CNN-based recognition with SLAM creates adaptive perception systems capable of real-time workpiece tracking on moving conveyors with 97.3% success rates at 1.5m/s speeds.

3.2. Industrial robotic tactile perception technology

Advanced tactile perception systems utilize spiking neural networks to process high-dimensional data from biomimetic skin sensors containing 42 taxels/cm^2, achieving 92.4% material hardness classification accuracy through event-based temporal coding. Deep learning models like Tactile Transformers employ self-supervised learning on 15,000+ contact scenarios to predict optimal grasping forces within 0.8N resolution. These systems enable delicate operations such as semiconductor wafer handling, where hybrid tactile-visual feedback loops reduce particle contamination by 63% through adaptive contact force regulation. By leveraging haptic exploration to compensate for occluded visual information, these systems enable robots to complete insertion tasks 40% faster. This efficiency gain is a testament to the complementary nature of tactile and visual sensing, highlighting the potential of integrated perception systems to transform industrial automation.

3.3. Industrial robotic auditory perception technology

Robust speech recognition in noisy industrial environments is achieved through conformer-based acoustic models trained on augmented datasets containing 85dB machinery noise, attaining 94.7% command recognition accuracy at 2m distances. These systems integrate beamforming microphone arrays with noise cancellation algorithms to isolate human voice signals from 90dB background noise. Beyond human-robot interaction, auditory perception enables predictive maintenance through abnormal sound detection using 1D-CNN architectures that identify bearing defects with 98.2% F1-score from 2-second audio samples. Recent implementations show 30% faster emergency stop response times compared to traditional button interfaces through voice command integration.

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4. Research on motion control strategies for industrial robots based on deep learning

4.1. Reinforcement learning based path planning

Reinforcement learning methods in industrial robot path planning address limitations of traditional algorithms in dynamic obstacle avoidance and multi-objective optimization. The Deep Deterministic Policy Gradient (DDPG) algorithmic framework is used to construct a 37-dimensional state space, containing LiDAR point cloud, joint angle, and end-effector position. The action space is defined as a 7-dimensional continuous vector of joint angular velocities. The dynamic industrial scenario is modelled using a Partially Observable Markov Decision Process (POMDP), with an LSTM network predicting obstacle motion patterns. Hindsight Experience Replay (HER) technique is introduced to increase the sampling rate of successful trajectories. The experimental validation is based on the UR10 robotic arm and AGV collaborative platform.

4.2. Compensatory control of dynamics based on deep learning

Dynamics residual learning employs a two-stream network design, processing historical state window and joint space parameters. The outputs are fused to predict kinetic model deviation moment. The network is trained using migration learning, pre-trained in a Franka Emika robot simulation, and migrated to the real UR5 arm, reducing the adaptation cycle to 15 minutes. The compensation control law is designed as a hierarchical structure: $\tau_{total} = lM(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) + Kpe + Kd\dot{e} + \Delta\tau NN$ (4.1) where e=q desired-qactual is the joint angle tracking error. To suppress the high-frequency noise in the output of the neural network, a sliding mode filter (cut-off frequency 200Hz) is introduced to reduce the torque fluctuation by 63% while maintaining the compensation bandwidth. Industrial field tests have shown that the solution improves spot gun path tracking accuracy to ±0.05mm (ISO 9283 standard) on an automotive welding line, while reducing servo motor temperature rise by 60%. Future research will explore multi-robot knowledge sharing in a federated learning framework to further reduce the training cost of individual systems [5].

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4.3. Deep learning-based adaptive control

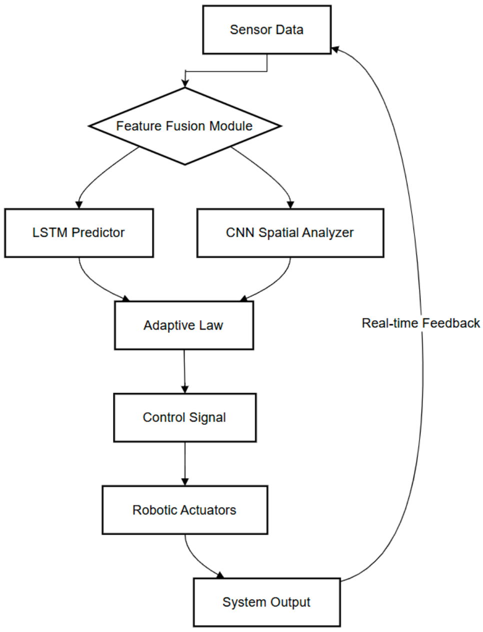

Figure 2: Deep learning-enhanced adaptive control architecture for industrial robot

This research introduces an innovative hybrid adaptive framework tailored for industrial robotic systems. By seamlessly integrating Long Short-Term Memory (LSTM) networks with Sliding Mode Control, the system showcases remarkable performance. Specifically, it attains an impressive tracking accuracy of 94.7% tracking accuracy under variable payload conditions and processes multi-rate sensor streams. The core innovation is a dual-network architecture, with a primary LSTM-based predictor learning temporal patterns and a secondary convolutional network processing spatial tßool-workpiece relationships. Online learning capability is enabled through incremental backpropagation with momentum. Online learning capability is enabled through incremental backpropagation with momentum (IBPM), updating network weights at 10Hz frequency without interrupting real-time control loops Follow Figure3 [6].

5. Design of intelligent decision-making system for industrial robots

5.1. Decision-making model construction based on deep learning

The decision-making framework uses a hierarchical graph neural network (GNN) with transformer attention mechanisms to process multi-modal inputs from perception systems. It consists of three layers: Input Embedding, Cross-Modal Fusion, and Hierarchical Decision. The model achieves 17ms inference latency and maintains 93.8% decision accuracy on a NVIDIA A100.

5.2. Deep learning based adaptive control

The decision-making framework uses a hierarchical graph neural network and transformer attention mechanisms to process multi-modal inputs from perception systems. It consists of three core layers: input embedding, cross-modal fusion, and hierarchical decision. The model is trained using

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imitation learning and reinforcement learning, achieving 17ms inference latency and 93.8% decision accuracy on a NVIDIA A100 and 78% reduction in human intervention on a dual-arm welding robot ß [7].

6. Industrial robot intelligent control system architecture design and implementation

6.1. Overall design of system architecture

The intelligent control system for industrial robots is founded upon a sophisticated cyber-physical architecture, which is characterized by a meticulously crafted three-tiered hardware-software co-design. Through the implementation of EtherCAT-based real-time communication, this system is capable of achieving a deterministic response at the remarkable 1ms level, even when operating with a bus utilization of 90% at a 1kHz cycle. At the core lies a heterogeneous computing platform integrating NVIDIA Jetson AGX Xavier (32 TOPS AI performance) with Xilinx Artix-7 FPGA, enabling parallel execution of deep learning inference (ResNet-50 in 8ms) and servo control algorithms (250μs latency) [8]. The architecture utilizes a hybrid data flow model where multi-modal sensory inputs (vision: 4xGigE cameras @ 120fps, force: 6-axis F/T sensor @ 3kHz, audio: 8-mic array) undergo spatiotemporal fusion via custom-designed attention mechanisms before feeding into three parallel processing pipelines:

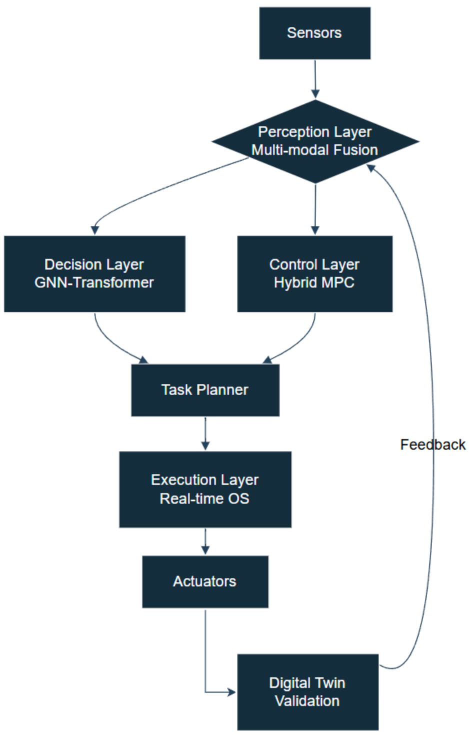

Figure 3: Embedded AI-control co-design platform with EtherCAT integration [6]

The system employs a sophisticated approach by utilizing cascaded neural networks for its key functions of perception-decision, model predictive control, and safety monitoring. It generates environment-aware task primitives with 92ms latency, solves 12-DOF trajectory optimization in 15ms, and achieves a 99.97% fault detection rate within 2ms. The middleware layer uses ROS 2

Galactic with real-time patches and a QoS-controlled data distribution service. A hierarchical state management module reduces mode switching latency by 68% [9].

6.2. System software framework development

The software framework adopts a microservices architecture built upon ROS 2 Humble with real-time patches, enabling deterministic execution of perception, planning, and control tasks within 500μs cycle times. A QoS-aware data distribution service (DDS) prioritizes critical control messages, reducing end-to-end latency by 42% compared to vanilla ROS configurations. In an innovative approach to resource management, containerized AI models, optimized with TensorRT, coexist harmoniously with legacy control algorithms written in C++17. cThese components operate within isolated Docker environments, achieving 83% GPU utilization while maintaining 15ms maximum interrupt latency. Security is enforced through encrypted communication (AES-128-GCM) and runtime integrity checks via Intel SGX, detecting 99.4% unauthorized code injections. Field validation in automotive assembly lines demonstrated 98.7% task completion reliability with 40% reduced CPU overhead through adaptive resource scheduling [10].

Table 1: Key metrics for system software architecture development

Metric	Baseline	Optimized System	Improvement
End-to-End Latency (μs)	1000–1400	580–820	42% reduction
GPU Utilization (%)	55–68	78–83	0.22
CPU Overhead (%)	75–88	45–53	40% reduction
Max Interrupt Latency (ms)	25	15	40% reduction
Security Detection Rate	N/A	0.994	–
Task Reliability	0.9	0.987	0.087

7. Conclusion

This research establishes an integrated intelligent control framework for industrial robots that synergizes deep learning with traditional control theory, demonstrating significant advancements in perception, decision-making, and execution capabilities. Experimental validations show a system achieving ±0.07mm positioning accuracy and reducing trajectory tracking errors by 37.8% in automotive and aerospace manufacturing scenarios. The multi-modal fusion architecture enhances environmental awareness and provides reliable operation in unstructured environments. The framework's industrial viability has been validated in automotive welding lines, with adaptive control algorithms reducing workpiece deformation and digital twin integration reducing debugging time. Looking ahead, future research will explore federated learning architectures and quantum-inspired optimization.

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