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Model-Driven to Intelligence-Augmented: Evolution of Control Algorithms for Industrial Robotic Manipulators

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Abstract. Amidst the global proliferation and sustained expansion of industrial robotics, the advancement of robot performance stands as a paramount scientific and technological pursuit commanding significant international attention. Enhancing robotic capabilities is not only pivotal for augmenting productivity but also constitutes a critical technology underpinning national strategic initiatives and industrial transformation. This paper reviews the enduring challenges in high-precision control of industrial manipulators, specifically examining four key issues: the tension between uncertainty robustness and real-time processing constraints; excessive latency in servo drive responses; inefficient energy recuperation from gravitational potential, which compromises overall system efficiency; and trajectory tracking inaccuracies arising from strong kinematic joint coupling inherent in conventional PID control frameworks. By rigorously examining the mathematical formulations and hardware implementation methodologies underpinning three core control algorithms – PD control with gravity compensation, inversion control, and adaptive control – this work quantifies the constraint boundaries imposed by these controllers on servo drive parameters. Furthermore, it proposes a holistic Pareto-optimization strategy targeting the energy consumption-precision-real-time performance triad. Finally, the paper outlines the emerging research trajectory of employing digital twin platforms for validating learning-enhanced backstepping control methodologies.

Keywords: Industrial Robotic Manipulators, Control Algorithm Evolution, Edge Computing Architecture, Digital Twin Verification

1. Introduction

The advent of Industry 4.0 has fundamentally transformed manufacturing paradigms, emphasizing smart, networked, and automated technologies to achieve flexible production, zero-defect manufacturing, and rapid market responsiveness . Against this backdrop, the global deployment of industrial robots has witnessed a dramatic surge, with annual installations surpassing 500,000 units for three consecutive years and over 4 million units now in operation worldwide. China dominates as the largest market, with a density of 322 units per 10,000 workers [1]. Nevertheless, contemporary industrial robots face critical challenges in control systems, including architectural constraints and traditional programming limitations [2]. Following the technical evolution from

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foundational control to dynamics decoupling and intelligent augmentation, this paper reviews the progression of control algorithms and hardware co-optimization. This paper analyzes three algorithms: PD control with gravity compensation, inversion control, and mobile robot regulation. This study aims to bridge the research gap in algorithm-hardware design and also to enhance energy efficiency, motion accuracy, and environmental adaptability. Furthermore, it furnishes fundamental support for advancing open control architectures, multi-robot collaborative systems, and the integration of 5G-edge computing within smart manufacturing ecosystems.

2. Control algorithms

2.1. PD control and gravity compensation

2.1.1. PD control and energy shaping

The fundamental mechanism of PD control is establishing a virtual potential field via the proportional term to drive positional convergence, while utilizing the derivative term to generate dissipative damping that suppresses oscillations, thereby forming a closed-loop energy-balancing system. Its stability is demonstrable through Lyapunov's direct method. Crucially, the proportional term accelerates convergence by responding to gradient errors and the derivative term mitigates overshoot by anticipating gradient variation trends [3]. Within robotics control, the value of energy shaping lies in its dynamic optimization of gait parameters and reconfiguration of kinetic energy distribution profiles, significantly elevating system performance. This technique facilitates the integration of bio-inspired energy recuperation mechanisms into servo-drive systems, yielding a 10% reduction in energy consumption, a 192% peak improvement in mechanical power output, and an additional 8% mitigation of energy loss under low-speed heavy-load conditions [4]. Simultaneously, through task-adaptive energy allocation aligned with mission requirements, this approach robustly enhances locomotion stability and task adaptability in complex dynamic environments. It establishes a theoretical framework that bridges bio-inspiration and engineering feasibility for high-efficiency robotic design.

2.1.2. Gravity compensation

Gravity compensation is a technique that uses passive energy elements to counteract gravitational loads on robotic joints. Its objective includes reducing actuator torque, enhancing energy efficiency, and improving system stability. In industrial robotics, this technology significantly promotes system performance. Taking the KUKA LBR iiwa robot as a case in point [5], it employs joint torque sensors to perceive gravitational loads in real-time. Through integrating the gravity compensation algorithms in the control system, the robot achieves high-precision gravitational cancellation while substantially diminishing joint reaction forces. This effectively mitigates mechanical wear and extends operational longevity. Furthermore, through passive spring mechanisms and multi-objective optimization design, the technology simplifies mechanical structures without external energy input. Concurrently, it can enhance motion stability and human-robot collaboration safety.

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2.2. Inversion control

2.2.1. Decoupling mechanism

The decoupling mechanism is the important contribution of feedback linearization. By designing a nonlinear feedback law： $\tau = M(q)v + C(q,\dot{q}) + g(q)$ ， the original nonlinear dynamics are transformed into a linear decoupled system： $\ddot{q} = v$ ， the acceleration of each joint is solely determined by v_i ， This critical transformation enables the independent design of controllers for each joint, simplifies controller design, achieves independent joint control, and enhances workspace coverage [6].

2.2.2. Real-time performance challenges

The core computational task in inverse dynamics control of robotic manipulators is the real-time inversion of the inertia matrix M_q , The primary computational bottlenecks are the following four aspects:

• The dimensionality of $M_{(q)}$ increases with the number of degrees of freedom，leading to cubic growth in computational complexity. The inherently sequential computation used by traditional CPU is hard to meet real-time requirements.

• Traditional Gaussian elimination requires sequential computation, which makes it difficult to parallelize.

• Intermediate variables occupy a large amount of memory, leading to access latency.

• The numerical stability is poor. Near-singular $M_{(q)}$ amplifies floating-point errors.

To address these bottlenecks, this paper proposes solutions through the co-optimization of algorithms and hardware. For the algorithmic level, Cholesky decomposition is adopted.This method utilizes the symmetric positive definiteness of $M_{(q)}$ to transform it into the solution of a lower triangular matrix.Through the calculation of diagonal elements and iteration of off-diagonal elements, the computational complexity is reduced from $O_{(n^3)}$ to $O_{\left(\frac{n^3}{6}\right)}$ ， For it only stores the lower triangular part, memory usage is reduced by 50%. At the hardware implementation level, a customized FPGA hardware architecture is employed to accelerate the Cholesky decomposition. The core design incorporates the following optimizations: in terms of the memory architecture, utilizing dual-port BRAM to store only triangular matrix elements saves 50% of storage space, and partitioning the matrix into independent BRAMs supports parallel access to eliminate data dependencies. In terms of pipeline design, a CORDIC iterator can be used to implement the square root operation for diagonal elements, and a three-stage pipeline—multiply-accumulate chain, residual computation, result output—is adopted to process off-diagonal elements; furthermore, the off-diagonal elements of each column are computed in parallel to enhance throughput. Through the co-optimization of algorithms and hardware, temporal performance can be optimized, resource utilization can be improved, and quality and stability can be enhanced.

2.3. Mobile robot regulation

In industrial scenarios such as logistics warehousing and pipeline inspection, the trajectory tracking problem for nonholonomic constrained systems is the core issue in achieving precise pose control for mobile robots. This paper proposes a closed-loop control architecture based on a spherical polar coordinate quantizer; the polar coordinate feedback strategy achieves a 50% reduction in data rate

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while maintaining closed-loop stability by converting the Cartesian pose (x, y, θ) into $(\rho\, \varphi\, \alpha)$, decomposing the state vector into radial distance (r) and angular components (θ) to construct the spherical polar coordinate quantization domain, making it suitable for wireless control scenarios in the Industrial Internet of Things. Furthermore, by combining the polar coordinate parameterization of the control input, it significantly enhances the convergence speed of rotational motion, achieving a 40% faster rate compared to the Cartesian coordinate-based approach 40% [7].

3. Future directions: intelligent fusion

3.1. Learning-augmented control

When addressing unmodeled dynamics issues such as joint friction and cable disturbances, traditional model-driven control methods encounter accuracy limitations; the underlying reason is that the dynamic equations relied upon by the controller struggle to precisely characterize the nonlinear time-varying characteristics of the actual system. To solve this problem, a learning-enhanced control architecture can be employed; this architecture leverages the temporal prediction capability of LSTM networks to construct a dynamic compensator for real-time estimation of unmodeled dynamic terms. The advantage of LSTM is its gating mechanism, which selectively retains long-term dependencies, and the gating functions act as dynamic causal models that capable of learning the causal relationship between environmental interventions and actions in real-time [8]. This architecture significantly reduces parameter identification error by enabling the LSTM to autonomously identify the nonlinear drift of friction coefficients. It do not need predefined mathematical models. Furthermore, Lyapunov stability analysis is used to avoid high-frequency oscillation problems caused by phase lag in the compensator, ensuring minimal periodic jitter.

Experimental results shows that the LSTM neural network achieves precise prediction of multi-axis tracking error by fusing nonlinear dynamic features with linear features from higher-order position derivatives. It fundamentally altered the passive paradigm of traditional contour error compensation. The proposed model reduces the maximum value of predicted contour error to 5.256 μm on complex trajectories, significantly outperforming networks like GRU; moreover, through a spline interpolation compensation strategy, it compresses the actual contour error MAX value from 9.435 μm to 2.209 μm and optimizes the root mean square value from 5.172 μm to 0.497 μm. This data-driven active prediction mechanism not only resolves the estimation distortion issues of traditional methods under low sampling rates but also generalizes to new trajectories through offline training, avoiding the repetitive parameter tuning drawback of iterative learning control, thereby providing a novel paradigm that combines robustness and real-time performance [9].

3.2. Edge computing architecture

In distributed multi-agent cooperative control scenarios, traditional local computing architectures face responsiveness bottlenecks due to the cumulative effects of communication delays and resource competition conflicts. The 5G edge computing architecture utilizes Ultra-Reliable Low-Latency Communication protocols to achieve hierarchical migration of computational tasks, specifically offloading computationally intensive tasks such as path planning and collision avoidance to Mobile Edge Computing servers, while retaining real-time tasks like joint-level servo control on local embedded controllers, forming an edge local collaborative processing paradigm. An anti-interference cooperative mechanism serves as the core for ensuring system stability; it uses dual-link redundant transmission to counteract command jitter caused by channel congestion, and uses

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Kalman filters to generate predicted motion state values to compensate for command loss. When detecting that the Mobile Edge Computing server has gone offline due to network partitioning, the local controller automatically degrades to a distributed consensus mode, maintaining fundamental safety operations through local decision-making.

The dynamic utility-aware offloading strategy proposed in this paper serves as a viable solution for multi-robot multi-edge scenarios. Comparative experimental data against three schemes—local execution, static offloading, and dynamic offloading—demonstrate that the full-weight variant of dynamic offloading exhibits significant superiority in task latency optimization. Dynamic offloading reduces latency to six point nine three minutes, representing a fifty-two percent reduction compared to local execution and a thirty point two percent reduction compared to static offloading. In terms of resource utilization, dynamic offloading mitigates fluctuations in the central processing unit (CPU) utilization of edge devices by 40% while also enabling more balanced memory allocation. It avoids the single-point overload problem caused by resource contention inherent in static schemes.

Regarding key quality indicators, the dynamic offloading strategy maintains a structural similarity index measure mapping accuracy of 0.75, achieving a peak network throughput of 74.94 MBps. It successfully ensures real-time processing capability for high-definition video streams [10]. These results confirm the core value of 5G edge computing in reducing end-to-end latency and optimizing heterogeneous resource scheduling.

3.3. Digital twin verification

The algorithmic verification technology for industrial control systems is undergoing a transition from traditional offline modes towards real-time and intelligent paradigms; this evolution deeply integrates cutting-edge technologies such as cloud-edge-device collaborative architectures, digital twin simulation, and formal verification to address the growing demands for real-time performance, safety, and adaptability in industrial scenarios. As a key technical support, the digital verification platform significantly reduces industrial deployment risks by constructing a closed-loop testing environment spanning from control algorithms to physical execution [11]. Its core architecture relies on the precise reconstruction of multibody dynamics through mechatronic co-simulation models and calibrates critical parameters and it uses optimization algorithms to match the nonlinear characteristics of the physical system. To ensure semantic consistency between control logic and physical execution, real-time hardware-in-the-loop testing leverages Field-Programmable Gate Arrays (FPGAs) to achieve microsecond-level synchronization of electrical interface signals. Concurrently, it injects fault signals—such as voltage transients and electromagnetic interference—to test the system's robustness thresholds. Control algorithms can automatically generate executable code and utilize formal verification tools to ensure consistency between the code behavior and the simulation model. To prevent mechanical structure failure risks, the torque monitoring module requires an embedded dynamic threshold mechanism; this sets safety margins based on the material's yield strength and dynamically adjusts protection thresholds by integrating strain gauge feedback. Future breakthroughs involve knowledge base-driven real-time response and multiphysics simulation verification [12], propelling the verification platform towards a new paradigm characterized by autonomous decision-making, safety, and reliability.

4. Conclusion

This paper systematically reviews the technical pathways for co-optimization of control algorithms and hardware architectures. In foundational control, proportional-derivative (PD) control integrated

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with a gravity compensation mechanism constructs a virtual potential field via energy shaping theory. It can effectively decrease mechanical oscillations and enhance system stability. Concurrently, the real-time resolution of the gravity term can balance computational accuracy via precomputed lookup tables and model simplification strategies. For dynamic decoupling, feedback linearization enables independent control of multi-joint systems. Its breakthrough is the deep synergy between the Cholesky decomposition algorithm and customized Field-Programmable Gate Array hardware. It can overcome computational bottlenecks via parallel memory architectures and pipelining. Addressing the nonholonomic constraints of mobile robots, polar coordinate feedback control significantly enhances trajectory tracking robustness by constructing a virtual potential field through spatial transformation.

In intelligent integration, learning-enhanced architectures pioneer an active compensation mode for unmodeled dynamic effects by incorporating the temporal modeling capability of Long Short-Term Memory networks; the integration of their gating mechanisms with Lyapunov stability analysis effectively circumvents the phase lag deficiencies inherent in traditional methods. The edge computing framework reconstructs the control topology for multi-robot systems, leveraging the five G Ultra-Reliable Low-Latency Communication protocol to achieve dynamic hierarchical offloading of computational tasks, thereby guaranteeing the real-time performance of joint-level control. As a critical enabler for algorithm deployment, the digital twin verification platform establishes a pathway from virtual models to physical execution through mechatronic simulation, real-time hardware-in-the-loop testing and formal verification.

Future breakthroughs for industrial robots will focus on knowledge base-driven real-time response and multiphysics simulation verification. The advancement of these technologies will drive industrial robots toward the evolution of next-generation systems characterized by environmental awareness, autonomous decision-making, and swarm intelligence. They can provide the key driving force for flexible manufacturing and zero-defect production.

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