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Research Progress and Performance Optimization Paths of Robot Adaptive Control Technology: A Review

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Abstract: As robot technology continues to expand into complex and dynamic scenarios, adaptive control technology has become a key means to address uncertainties such as system parameter settings and external disturbances. This paper systematically reviews the research progress in this field. Breakthroughs have been achieved in algorithm theory, including nonlinear system control, constraint optimization, and integration with intelligent algorithms. In terms of scenario applications, differentiated solutions for mobile, special-purpose, and industrial robots have been established. In the aspect of cooperative control, the dynamic coordination technology for multi-robot systems has been advanced. The current technical bottlenecks are summarized as follows: the trade-off between algorithm convergence and robustness, the mismatch between dynamic modeling and actual working conditions, the difficulty in optimizing control resources under multi-constraint conditions, and the insufficient cross-domain integration. To address these bottlenecks, optimization paths based on intelligent algorithm fusion, data-model hybrid modeling, multi-objective optimization, and modular architecture reconstruction are proposed. This study can provide theoretical references for the scenario-based implementation and performance improvement of robot adaptive control technology, and promote its large-scale application in complex environments.

Keywords: Robot Adaptive Control; Performance Optimization; Intelligent Algorithm Fusion; Dynamic Modeling; Multi-Robot Cooperation

1. Introduction

Robot technology, originally mainly applied in assembly lines of traditional manufacturing industries, has gradually expanded to complex scenarios such as medical care, aviation manufacturing, and post-disaster rescue[1]. Due to the core requirements for operational accuracy and environmental adaptability, traditional fixed-parameter control methods are inadequate in dealing with uncertainties like system parameter perturbations and external disturbances[2]. Adaptive control technology, relying on a closed-loop mechanism of real-time perception and dynamic adjustment, has become a crucial approach to ensure the stable performance of robots[3]. In recent years, numerous achievements have been made in this field, ranging from nonlinear adaptive algorithms based on function approximation to human-machine interaction control schemes integrated with fuzzy logic, and the technical system is constantly improving[4]. However, existing studies still have limitations. For instance, most reviews focus on a single field, lacking cross-dimensional sorting, and the correlation analysis between "technical progress" and "performance optimization" is insufficient, making it difficult to form a complete set of solutions[5]. Based on this situation, this paper integrates domestic and foreign research results following the logical chain of "theoretical progress - bottleneck analysis - optimization paths" to provide guidance for future research in this field.

2. Core Research Progress of Robot Adaptive Control Technology

2.1 Theoretical Breakthroughs in Adaptive Control Algorithms

Adaptive control algorithms have been developed around the goal of "improving accuracy and stability in uncertain scenarios", and key progress has been made in three aspects in recent years. For the nonlinear dynamic problems faced by continuum robots and manipulators, Xu et al.[6] designed an AFATC strategy without update laws using function approximation technology. The stability was verified based on Lyapunov theory, and the results showed that the trajectory tracking error was reduced by more than 30% compared with traditional methods. Wang et al.[7] established the connection between nonlinear systems and linear dynamics by means of "forward stepping design + inertia invariance", achieving asymptotic convergence of parameter estimation errors. In the field of constraint optimization, Mendoza et al.[8] designed an adaptive controller based on constrained BLF for hybrid Cartesian-Delta robots. This controller takes into account both the end-effector position and joint limits, and its tracking accuracy is 40% higher than that of PID. Zhang et al.[9] combined the integral barrier Lyapunov function with RBFNN to solve the problems of actuator saturation and unknown disturbances in nonholonomic mobile robots, which can still maintain a stable state even in scenarios with sudden load changes. In terms of intelligent algorithm fusion, Valdez et al.[10] proposed an architecture of "adaptive fuzzy controller+robust generalized predictive controller" for human-machine interaction scenarios such as manipulator-assisted rehabilitation training and precision assembly. The fuzzy controller can cope with the randomness of human movements by dynamically adjusting the rule base, while the generalized predictive controller can optimize the control input in advance to avoid interactive force overload and improve operational safety. Guo et al.[11] integrated neural network adaptive compensation for environmental force disturbances with spatial iterative learning to optimize trajectories for unknown environment interaction scenarios such as flexible workpiece assembly. The signal convergence was verified using Lyapunov theory, and rapid reduction of interactive force tracking errors was achieved in experiments.

2.2 Application Research for Different Task Scenarios

2.2.1 Mobile robots

The research on path tracking and control of mobile robots focuses on the integration of "planning - tracking". Tika et al.[12] proposed a scheme combining an MPC feedback controller with Bayesian optimization for omnidirectional mobile robots, which results in a tracking error of less than 5% and enables maximum speed. Jin et al.[13] considered the case of actuator failures and designed an adaptive fault estimation and backstepping control strategy to verify the tracking stability under fault conditions.

2.2.2 Special-purpose robots

The research on rehabilitation exoskeletons and legged robots focuses on improving robustness. Brahmi et al.[14] designed a robust adaptive sliding mode controller for the unknown dynamics and disturbances of rehabilitation exoskeletons, achieving high-precision tracking of gait trajectories, and the sliding mode surface can converge within a limited time. Sombolestan et al.[15] integrated adaptive control into the quadratic programming force control of legged robots, reducing the leg force fluctuation by 25% when walking on complex terrain. Pi et al.[16] proposed an adaptive sliding mode control method for jumping robots, with an attitude error of less than 3°.

2.2.3 Industrial robots

The adaptive servo control of industrial robots mainly focuses on load changes and error suppression. Danis et al.[17] introduced an integral term into the 6-degree-of-freedom manipulator. When the load increases from 5 kg to 15 kg, the position error sensitivity is reduced by 60% compared with non-adaptive methods. Liu et al.[18] derived a parameter estimation law based on the Newton-Euler model and Lyapunov theory, which has better trajectory tracking accuracy than traditional PPI control.

2.3 Multi-Robot Cooperative Adaptive Control

The application of multi-robot clusters has promoted the development of cooperative adaptive technology. In the field of path planning, Tang et al.[19] proposed a cooperative evolution PSO method, updating particle parameters through an adaptive strategy. In multi-obstacle scenarios, the optimal solution acquisition rate is increased by 35% compared with standard PSO. Murata et al.[20] combined FCP gait with Timekeeper control for hexapod robots, achieving stable walking on complex terrain

3. Current Technical Performance Bottlenecks and Core Challenges

3.1 Trade-off between Algorithm Convergence and Robustness

Existing algorithms generally face the

"speed-stability" contradiction. Increasing the adaptive gain to improve the convergence speed tends to cause high-frequency oscillations of the system, affecting operational accuracy. Introducing conservative constraints to ensure robustness will prolong the response time and slow down the operational efficiency. For example, in the AFATC strategy proposed by Xu et al.[6], when the load mutation frequency exceeds 0.5 Hz, the convergence time is extended to 0.8 s, which is difficult to match the sorting rhythm of 120 times per minute for electronic components, directly leading to a 15% decrease in sorting efficiency. In Wang H's [9] method, when the external disturbance exceeds 5 N·m, the robustness is significantly attenuated, and the tracking error increases from 0.05 mm to 0.14 mm, exceeding the error threshold of ±0.1 mm for precision machining. This contradiction is more prominent in high-speed and precision scenarios, seriously limiting the application scope of the technology.

3.2 Mismatch between Dynamic Modeling and Actual Working Conditions

The accuracy of adaptive control depends on the accuracy of the model. However, "unmodeled dynamics", such as joint friction and flexible deformation, will lead to a disconnect between the model and actual working conditions. In the industrial robot control scheme proposed by Liu Jiale et al., when the joint angular velocity is greater than 10 rad/s, the tracking error under high-speed working conditions is 3 times larger than that under low-speed working conditions due to the failure to consider flexible deformation. In the rehabilitation exoskeleton control by Brahmi et al.[14], the human muscle tension changes, requiring frequent parameter adjustments, which reduces the control stability.

3.3 Difficulty in Control Resource Optimization under Multi-Constraints

Robots usually face multi-objective constraints such as "accuracy-energy consumption-safety" during operation, but their resources such as computing power and communication bandwidth are limited. In the mobile robot control scheme proposed by Zhang et al.[21], the computational load is increased by 40% to maintain accuracy, resulting in response delays of edge devices. In the MPC adaptive control by Tika et al.[12] in multi-robot cooperation, the parameter tuning cycle is extended to 1.2 s due to limited communication bandwidth, which is difficult to meet the real-time requirements.

3.4 Insufficient Cross-Domain Technology Integration

Adaptive control technology presents a situation of "domain isolation". For example, Zhao et al.'s [22] research on multi-mode mobile robot control shows that with the rapid development of mobile robot technology, traditional single-motion-mode mobile robots can hardly meet the application requirements in complex environments, and multi-mode mobile robots have become a research hotspot due to their excellent environmental adaptability and task execution capabilities. This study reviews the research progress of multi-mode mobile robots in the past 15 years, focusing on key technical challenges and future development directions.

4. Key Paths for Robot Adaptive Control Performance Optimization

4.1 Control Upgrade Based on Intelligent Algorithm Fusion

The "adaptive control+AI" approach is used to break through the "convergence - robustness" contradiction. Firstly, reinforcement learning is integrated into sliding mode adaptive control, and the gain parameters are optimized by Q-learning, which can increase the convergence speed of jumping robots by 30% and reduce the oscillation amplitude by 25%. Secondly, combined with the robot control large model, the bionic robot scheme proposed by Hoejin et al.[23] predicts disturbances through the model, shortening the response delay to less than 0.1 s. Thirdly, the "fuzzy logic+generalized prediction" architecture is adopted, and in the human-machine interaction of manipulators, the tracking error is less than 0.5 mm and the interactive force fluctuation is less than 2 N.

4.2 Data-Model Hybrid Modeling Method

Data-driven methods are used to complement model deviations. The first is "offline pre-training+online correction". For example, the AFATC strategy proposed by Xu et al.[6] combines an offline function approximator, which greatly improves the matching degree of the continuum robot model by 40%. The second is real-time data feedback modeling. For instance, the spatial iterative learning control method adopted by Guo et al.[11] modifies the environmental model using interactive force data, reducing the mismatch rate by 35%. The third is multi-source data fusion. For example, the vision-motion fusion scheme proposed by Zhang et al.[21] effectively solves the slip error problem of omnidirectional mobile robots, improving the tracking accuracy by 50%.

4.3 Control Strategy Design for Multi-Objective Optimization

Resource allocation is carried out in multi-constraint scenarios, mainly in the following aspects. The first is multi-objective parameter tuning. Danis et al.[17] optimized the integral term and gain for the 6-degree-of-freedom manipulator using NSGA-II, reducing the error by 20% and energy consumption by 15%. The second is dynamic resource allocation. The cooperative PSO method proposed by Tang et al.[19] allocates computing power according to the operational accuracy requirements, improving the multi-robot planning efficiency by 30%. The third is hierarchical constraint processing. The CBLF controller adopted by Mendoza et al.[8] first meets the safety constraints and then optimizes the accuracy, achieving no overshoot and an error of less than 0.3 mm.

4.4 Modular Architecture Reconstruction

The cross-domain integration capability can be improved from the following aspects. Firstly, in terms of modular interface design, the parallel robot framework proposed by Shaymaa et al.[24] can increase the reusability of adaptive algorithms by 60%. Secondly, the construction of a scenario strategy library. In recent years, reinforcement learning has gradually expanded from single-agent decision-making to multi-agent collaboration and game theory, forming the research hotspot of multi-agent reinforcement learning. A multi-agent system consists of multiple entities with autonomous perception and decision-making capabilities, which is expected to solve large-scale complex problems that are difficult to handle by traditional single-agent methods. Multi-agent reinforcement learning not only needs to consider the dynamics of the environment but also deal with the uncertainty of other agents' strategies, thereby increasing the complexity of the learning and decision-making process. This framework can also shorten the cross-domain task adaptation time to less than 0.5 hours and upgrade the human-machine collaboration architecture. In addition, the rehabilitation exoskeleton control by Brahmi et al.[14] adopts the design of "interaction layer-control layer-execution layer", with a strategy adjustment response time of less than 0.2 seconds, improving patient comfort.

5. Conclusion

This paper sorts out the three-dimensional development of "algorithm-scenario-cooperation" in robot adaptive control technology, clearly identifies the four major bottlenecks of "convergence-robustness trade-off, modeling mismatch, resource optimization, and cross-domain integration", and proposes corresponding optimization paths. In the future, this field will develop in three directions: first, the end-to-end integration of AI large models and adaptive control to solve the lag problem in dynamic scenarios; second, edge computing to empower real-time control to meet the high-speed collaboration needs of multi-robot systems; third, the integration of brain-computer interfaces and force-tactile feedback to improve the safety of human-machine interaction. These breakthroughs can promote the large-scale application of adaptive control technology in complex scenarios and provide support for industrial intelligence and social service upgrading.

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