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The Research Progress on Adaptive PID Control Methods in Joint Space of Robotic Arms

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Abstract. The spatial coordination of robotic arm joints represents a significant obstacle in robotics. Despite its simplicity, traditional PID control is still extensively used owing to its straightforward implementation and dependable performance in many practical applications. However, traditional PID control has certain limitations when dealing with nonlinear, time-varying systems or complex environments. Thus, adaptive PID control effectively enhances the robustness and adaptability of the system by adjusting the gain parameters online. This paper reviews recent advances in adaptive PID control for robotic arm joint space, focusing on approaches such as online parameter tuning, model reference adaptive control (MRAC), and intelligent optimization techniques. The results show that online adjustment and MRAC methods have strong robustness in nonlinear and disturbed environments. The intelligent optimization method performs outstandingly in enhancing accuracy and response speed, but faces challenges in computational complexity and real-time performance. Moreover, the limitations of existing research are also discussed, and the future application prospects of combining deep learning and reinforcement learning with adaptive PID control are explored.

Keywords: Robotic Arm, Joint Space Control, Adaptive PID Control, Model Reference Adaptive Control (MRAC), Intelligent Optimization

1. Introduction

Robotic arms, widely employed in manufacturing, healthcare, and services, are essential to modern automation. Their efficiency relies on precise, stable control, typically achieved through joint space control, which guides movement by adjusting joint torques or angles. In addition, it offers low computational complexity and strong real-time performance, making it especially well-suited for controlling robotic arms with many degrees of freedom. However, due to the nonlinearity, strong coupling and external disturbances of the robotic arm system, the traditional PID control method has certain limitations in high-precision control tasks. To enhance the accuracy and robustness of robotic arm control, researchers have proposed a series of adaptive PID control strategies, such as sliding mode adaptive PID, fractional PID, and event-triggered adaptive PID. These methods have enhanced traditional PID control by improving nonlinear suppression, handling high-frequency interference, and boosting computational efficiency to better cope with complex, dynamic working environments. Intelligent optimization methods, such as fuzzy logic, evolutionary algorithms, and reinforcement learning, are increasingly used to tune PID parameters, hence improving robotic arm

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control adaptability and stability. Despite experimental successes, accuracy, real-time performance, and robustness in robotic arm control remain challenging. Especially when dealing with factors such as system nonlinearity, load changes and external disturbances, how to design more efficient and stable control strategies remains the focus of current research. This paper explores an adaptive PID control method combining online adjustment, model reference adaptive control, and intelligent optimization, analyzing its effectiveness in robotic arm control to offer valuable insights for precise and practical applications.

2. Pid-based approaches for joint space control of robotic arms

2.1. The basic framework of joint space control

By adjusting the driving torque or joint angles, joint space control allows the robotic arm to follow a predetermined trajectory. It is suitable for real-time control of robotic arms with high degrees of freedom. Compared to Cartesian control, joint space control operates directly on joint variables with lower computational complexity. The robotic arm's dynamics are usually modeled by the Lagrange or Newton-Euler method, with the Lagrange method preferred for its clarity and ease of analysis. The kinetic equation is shown below:

$$\tau = M(q)\ddot{q} + C(q, \dot{q}) + G(q) + \tau_{EXT} \tag{1}$$

where q is joint angular displacement vector, $M(q)$ is inertial matrix, $C(q, \dot{q})$ is Coriolis force matrix, $G(q)$ is gravity, τ is control input, or joint driving torque. The dynamic equation of a robotic arm is highly coupled and nonlinear, requiring control algorithms that carefully consider these dynamics to maintain stability and accuracy. Among feedback-based methods, PID control remains a classic and effective approach for stable joint movement.

$$u(t) = K_p e(t) + K_i \int e(t) ft + K_d \frac{de(t)}{dt} \tag{2}$$

where e is tracking error, K_p , K_i , K_d is proportional, integral and differential gain parameters. The proportional term adjusts joint torque based on the error, speeding up the response. The integral control term corrects the system deviation through cumulative error and improves the steady-state accuracy. The differential term predicts error trends to improve the system's dynamic response. PID control, with its simple structure and ease of implementation, is widely used in robotic arm joint control. However, due to nonlinearity and disturbances, PID alone cannot ensure high precision. Combining feedforward, adaptive, or model-based methods enhances control and robustness.

2.2. The application of traditional PID control in robotic arms

Traditional PID control is widely used in joint space control, especially for rigid robotic arms with high stiffness and well-defined dynamics. In the trajectory tracking task of the SCARA robotic arm, PID control can keep the steady-state error within 0.1°, but when the load suddenly changes, the overdrive can reach 10%, increasing the stabilization time [1]. The PID control in rigid robotic arms is mainly limited by the fact that the fixed gain parameters are difficult to adapt to the changes in load and motion state, resulting in an increase in overloading and steady-state errors. Elasticity in flexible manipulators causes nonlinear dynamics and phase lag, leading to low-frequency resonance

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and reduced PID effectiveness. Under varying loads, steady-state errors can reach 0.5°, five times higher than the 0.1° typical of rigid robotic arms[2]. In the grasping task of the flexible robotic arm, the grasping success rate of the traditional PID control was only 76%, while it increased to 91% after adopting the adaptive PID, indicating that the flexible robotic arm requires a more adaptive control strategy [3]. Its main limitation is that stiffness variations compromise control accuracy. The fixed-gain PID is prone to cause low-frequency oscillation and reduce the stability of the system. The rigid manipulator, governed by inertia and Coriolis forces, achieves stable performance through fixed-gain PID control. Flexible manipulators suffer tracking accuracy degradation from load-induced stiffness variations caused by elastic deformation and nonlinear dynamics. While fixed-gain PID proves inadequate for such cases, flexible arms benefit more from adaptive control or model compensation strategies to improve both accuracy and robustness.

3. Classification and principle of adaptive PID control methods

3.1. The adaptive PID control based on online parameter adjustment

Online parameter tuning enhances the robustness and tracking performance of control systems in nonlinear and disturbed environments by real-time updating the gain parameters (K_p , K_i , K_d) of the PID controller. Early methods employed the gradient descent approach to dynamically optimize parameters by minimizing the control error function, but their slow convergence and tendency to get stuck in local optima limited their application in rapidly changing scenario [4]. To improve update efficiency, model predictive control (MPC) mechanisms have been introduced in recent years, applying its rolling optimization concept to PID parameter adjustment, making the control more forward-looking and adaptive [5]. In a six-degree-of-freedom robotic arm experiment, this strategy reduced the root mean square tracking error by approximately 35%, greatly improving the system's response speed and control accuracy. Besides, the recursive least squares (RLS) method has also been used for online identification of system dynamic characteristics and guiding real-time PID parameter updates, effectively enhancing the stability and real-time performance of parameter adjustments [6]. This method suits high-frequency disturbances. However, MPC demands high computational power, whereas RLS needs noise filtering for robustness.

3.2. PID regulation based on Model Reference Adaptive Control (MRAC)

Model reference adaptive control (MRAC) constructs an ideal reference model and dynamically adjusts the controller parameters based on the error between the actual system output and the model output, making the system behavior approach the reference model. It is suitable for control objects with uncertainties or time-varying characteristics[6]. In the traditional MRAC-PID architecture, the PID controller is embedded in the adaptive framework, and the adaptive law is constructed based on Lyapunov stability theory, effectively enhancing the stability and tracking performance of the system under nonlinear disturbances. Experiments show that this method can significantly improve the control accuracy of the robotic arm in the presence of friction and modeling errors. However, this strategy heavily relies on the system dynamics model and its performance degrades when faced with unmodeled dynamics or major parameter variations. To enhance the adaptability to model uncertainties, the neural network enhanced MRAC-PID method has been proposed, which embeds a neural network to estimate and compensate for unmodeled dynamics in real time, improving control accuracy and system robustness [7]. In robotic arm grasping experiments, this method maintained ±0.1° angle accuracy despite around 20% model error, showing strong adaptability to complex

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conditions. Additionally, the distributed MRAC method independently designs reference models for each joint of the multi-joint system, achieving distributed adaptive regulation, reducing the computational burden of centralized processing and improving the scalability of the system [8]. This strategy is particularly suitable for high-dimensional systems such as multi-degree-of-freedom robotic arms and modular robots. Although MRAC and its variants provide strong adaptability and theoretical stability, they depend on dynamic models and need parameter tuning at initialization. Besides, extensions involving neural networks or distributed architectures increase computational complexity, impacting real-time performance and hardware demands [8]. Therefore, in resource-limited or model-scarce scenarios, applying MRAC requires careful evaluation.

3.3. Adaptive PID control based on intelligent optimization

As control systems grow more complex, fixed-parameter PID controllers struggle with nonlinearity and changing conditions, hence limiting accuracy and response speed. To improve adaptability and robustness, intelligent optimization has been applied to replace or support traditional tuning, driving the development of adaptive PID strategies. Fuzzy logic control dynamically tunes PID gains using error and its rate of change, requiring no precise model and effectively handling nonlinear systems [9]. This method achieved sub-millimeter accuracy and improved response in trajectory tracking, ideal for industrial settings with known structures yet complex models. Meanwhile, evolutionary algorithms like genetic algorithms (GA) and particle swarm optimization (PSO) perform offline PID parameter optimization by simulating natural selection or group collaboration to find global optima and avoid local traps. By mimicking natural selection or group collaboration, they explore complex search spaces to find global optima and avoid local traps. Due to high computational costs and lengthy optimization, these methods are unsuitable for real-time updates and are primarily used for parameter tuning before controller deployment. To address the real-time issue, reinforcement learning (RL) has been applied to the online optimization of PID parameters, capable of achieving adaptive control in complex environments without the need for system models [10]. By introducing the deep deterministic policy gradient (DDPG) algorithm, the controller can learn the optimal parameter strategy through interaction with the environment, achieving precise control with an overshoot of less than 5% under dynamic loads. Despite strong generalization and adaptability, reinforcement learning requires extensive data and computing power, with convergence stability still challenging in practice.

3.4. Other adaptive PID control methods

To improve accuracy and robustness under specific conditions, adaptive PID control adopts targeted strategies. Nonlinear disturbances are better suppressed by sliding mode adaptive PID, high-frequency interference is more effectively managed by fractional-order PID, and computational efficiency is increased through event-triggered adaptive PID. Sliding mode adaptive PID merges sliding mode control's robustness with PID's simplicity, making it ideal for systems with strong nonlinearity and significant external disturbances. This method introduces a switching function in the control law, enabling rapid suppression of system disturbances and enhancing the adaptability to model uncertainties [11]. Although this method has good tracking performance, due to the frequent switching of control inputs, it is prone to high-frequency jitter phenomena. To alleviate this problem, boundary layer technology is introduced in sliding mode control, smoothing the switching function to effectively reduce the amplitude of high-frequency jitter. Experimental results show that this improved method can reduce the end-jitter amplitude of industrial robotic arms by approximately

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60%, while maintaining robustness and significantly improving the stability and service life of the actuator [12]. Fractional-order PID control (FOPID) expands the parameter dimension of traditional PID through the introduction of fractional calculus operators, enabling the controller to have more flexible dynamic response capabilities [13]. This method outperforms integer-order controllers in suppressing high-frequency disturbances and system robustness. Recently, FOPID has integrated adaptive mechanisms with online order adjustment, effectively improving the system's dynamic adaptability [14]. In the vibration control experiments of flexible robotic arms, this method achieves a system energy attenuation rate of up to 98%, significantly accelerating the vibration convergence speed and improving control smoothness, especially suitable for complex systems such as elastic linkage structures and compliant robots. To address the issue of excessive computational resource consumption in traditional adaptive PID control, event-triggered adaptive PID control strategies have emerged. They trigger parameter updates only when the system error or state change exceeds the set threshold, avoiding redundant calculations caused by periodic updates [9]. This method uses an error-threshold trigger, adjusting gains only when errors exceed a set range, reducing controller load. In high-precision servo experiments, it cut CPU usage by ~40%, boosting efficiency while maintaining accuracy, ideal for resource-constrained settings like embedded and edge computing.

4. Performance comparison and development challenges of adaptive PID methods

4.1. Performance comparison of different methods

Table 1 summarizes the performance of several common adaptive PID methods across convergence speed, robustness, computational complexity, and applicable scenarios. These methods demonstrate marked differences in each aspect and are suited to different types of control tasks.

Table 1. Performance comparison of different adaptive PID methods

Method	Convergence Speed	Robustness	Computation Complexity	Application
Online parameter adjustment	Moderate	Moderate	Low	Changing load, low speed
MRAC-PID	Fast	High	High	High accuracy, known model
Fuzzy Adaptive PID	Slow	High	Moderate	Nonlinearity, external disturbance
Intelligent Optimization (GA/PSO)	Very slow	Moderate	Very high	Offline parameter tuning
Sliding mode adaptive PID	Fast	Very high	moderate	Strong disturbance and high robustness requirements

As shown in the table, MRAC-PID excels in convergence speed and robustness, making it well-suited for precise control in systems with known models. However, its computational complexity is relatively high, and it has high requirements for the accuracy of the reference model. The fuzzy adaptive PID controller is notably robust, particularly in handling nonlinear systems and strong external disturbances. However, its slower convergence speed limits its effectiveness in high-speed applications. Ideal for high-robustness and disturbance-rich environments, sliding mode adaptive PID must still address the drawback of chattering. Intelligent optimization methods, such as GA and PSO, can provide better offline parameter configurations, but their computational complexity is too high to meet the requirements of real-time control. Further studies have confirmed the performance variations among different methods. For example, the online parameter adjustment, MRAC-PID,

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and fuzzy adaptive PID methods have respectively improved accuracy, reduced overshoot, and enhanced precision in robotic arm trajectory and load control experiments [5,7,9].

4.2. Main challenges and future development

Technical challenges still persist in adaptive PID control methods. Firstly, a major limitation is the reliance on accurate dynamic models, particularly in methods like MRAC, online parameter tuning, and sliding mode control, which restricts their effectiveness in complex or uncertain environments. Secondly, intelligent optimization methods such as genetic algorithms, particle swarm optimization, and deep deterministic policy gradient can boost control performance, but their high computational demands make real-time application difficult, especially in embedded systems. Furthermore, current research mainly targets single metrics like tracking error, neglecting multi-objective optimization of energy efficiency and smoothness vital for industry. Future trends include deep learning-based adaptive PID control for model-free online adaptation in high-dimensional nonlinear systems [15]. They also involve integrating reinforcement learning methods such as Q-learning and DDPG with PID control to optimize gain adjustments for improved accuracy in dynamic environments [16]. Additionally, there is growing emphasis on multi-objective optimization using Pareto optimality to balance error, energy consumption, and vibration [17]. Finally, development focuses on adaptive PID architectures for emerging platforms such as flexible robotic arms and redundant degree-of-freedom systems to enhance adaptability and precision in complex settings.

5. Conclusion

By incorporating online tuning, intelligent algorithms, and advanced control theories, adaptive PID control greatly improves the adaptability and precision of robotic arm joint space control. However, model dependence, computational complexity, and multi-objective optimization remain challenging issues that need to be addressed. In the future, the integration of deep learning and reinforcement learning into intelligent PID control is anticipated to transcend traditional frameworks, offering innovative approaches for controlling robotic arms in complex and dynamic environments. Though adaptive PID control has progressed from simple parameter tuning to multidisciplinary integration, its effectiveness in complex scenarios remains limited by challenges in algorithm generalization, computational efficiency, and multi-objective optimization. With the advancement of deep learning and edge computing, intelligent adaptive PID is expected to evolve into a fully integrated system that unifies perception, decision-making, and control, thus offering essential technical support for high-end applications like surgical robots and robotic arms used in space exploration. In addition, the swift growth of open-source platforms like ROS-Control is set to accelerate the deployment of algorithms and drive the intelligent transformation of robotic systems in the Industry 4.0 era.

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