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High-Precision Trajectory Tracking Technology for Dual-Axis Robotic Arms based on Higher-Order Sliding Mode Control

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Abstract. Against the backdrop of rapid progress in industrial automation and intelligent manufacturing, this paper presents a hierarchical fusion control strategy that combines High-Order Sliding Mode Control (SOSM), deep learning, and Model Predictive Control (MPC) to address the critical bottlenecks of traditional Proportional-Integral-Derivativ (PID) control in dual-axis robotic arms, including initial trajectory deviation, residual vibration, and model uncertainty. The robotic arm is physically modeled using SolidWorks, imported into Sysplorer for dynamic simulation, and the control module is developed via Syslab. A well-designed sliding mode surface and exponential convergence law are adopted to realize robust SOSM control, while a dual-layer Long Short-Term Memory (LSTM) network is introduced to compensate for model uncertainties such as friction and vibration. A hierarchical control architecture is constructed: the upper layer uses MPC for 50 ms global trajectory planning, and the lower layer applies SOSM for real-time tracking with a 0.01 s sampling period, balancing global optimization and real-time response. Experimental results confirm that the proposed strategy outperforms conventional PID control in trajectory tracking precision, dynamic response, and robustness, providing a high-precision and robust control scheme for industrial applications. This work contributes to the technological innovation and engineering application of control system theory, robotics, artificial intelligence, and automation technologies, enriches the technical reserve of cross-field integration, and provides a reference for academic exchanges, technical demonstrations, and industrial cooperation in related cutting-edge fields, so as to boost global knowledge sharing and collaborative innovation.

1. Introduction

With the rapid development of industrial automation and intelligent manufacturing[1], robotic arms have become core execution equipment in automated production lines, flexible manufacturing cells[2], and intelligent assembly workshops due to their advantages of precise operation, high repeatability, and high reliability. Trajectory tracking accuracy, as a core performance indicator of robotic arms, directly determines operational quality, positioning efficiency, and system stability. As the simplest in structure and most widely applied basic motion unit, dual-axis robotic arms are extensively utilized in scenarios such as point grasping, simple trajectory simulation, and periodic reciprocating motions, with their control performance serving as the foundation for research on high-precision control of multi-degree-of-freedom robotic arms.

Currently, traditional PID control algorithms are widely adopted in industrial fields due to their simplicity and ease of implementation. However, these algorithms suffer from three major drawbacks that are difficult to overcome. Firstly, there is a significant trajectory deviation during the initial stage, and the PID parameters are fixed, making them unable to adapt to dynamic loads and changes in operating conditions. Secondly, joint flexibility and structural inertia tend to induce residual vibrations at the end-effector, resulting in long oscillation times and large steady-state errors during the stopping

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and positioning phase. Lastly, model uncertainties such as friction characteristics, load variations, and joint clearances continuously degrade control performance and reduce robustness. These issues collectively limit the application of dual-axis robotic arms in high-precision assembly, precision inspection, micro-manipulation, and other scenarios

In the realm of robotic arm trajectory tracking control, extensive research has been conducted by scholars both domestically and internationally, focusing on robust control, intelligent compensation, and hierarchical planning. International research, which commenced earlier, has established a mature system in areas such as optimization of sliding mode control theory[3], design of disturbance observers, and engineering application of model predictive control, with an emphasis on industrial-grade stability and reliability. Conversely, domestic research has concentrated on localization alternatives, cost-effective solutions, and the integration of multiple algorithms, achieving notable advancements in adaptive sliding mode control[4], fuzzy contro[5], active disturbance rejection control, and deep learning compensation, thereby formulating a technical pathway tailored to local industrial scenarios. Although existing studies have achieved breakthroughs in individual performance metrics, there remains a notable scarcity of comprehensive control strategies that simultaneously address initial accuracy, vibration suppression efficacy, and robustness.

This paper proposes a hierarchical trajectory tracking strategy that integrates high-order sliding mode control, deep learning compensation, and model predictive control. In accordance with the research objectives of high-precision tracking, vibration suppression and strong robustness, the methodology is designed based on three theoretical principles: Sliding mode control theory is adopted to improve disturbance rejection; Time-series deep learning is used to model and compensate uncertainties; Hierarchical model predictive control is applied to balance global optimization and real-time performance. High-order sliding mode control is employed to replace traditional PID control, enhancing robustness;a well-designed dual-layer LSTM network compensates for uncertainties such as friction and vibration; a dual-layer LSTM network is used to compensate for uncertainties such as friction and vibration; the upper layer MPC is utilized for global trajectory optimization,and the lower layer SOSM achieves fast real-time tracking with a guaranteed time-scale synchronization mechanism,while the lower layer Second-Order Sliding Mode Control (SOSM) achieves rapid real-time tracking, forming a control architecture that combines high precision, fast response, and strong disturbance rejection.The Lagrangian dynamic equation is established to accurately describe the robotic arm dynamics, and the computational complexity is analyzed to verify real-time executability under 0.01s sampling period. Through simulation and comparative experiments, it is verified that this scheme can effectively address the shortcomings of traditional control, providing a feasible technical path for high-precision trajectory tracking of dual-axis robotic arms.

2. Modeling and Key Technologies of Dual-Axis Manipulators

2.1 Overall framework of model design

In SolidWorks, the design of mechanical arm links, joints, and other components is completed. Material properties such as density and elastic modulus are set. The model assembly is achieved through the assembly function, and the parameters of joints and links are defined, as shown in Figure 1.



Figure 1. Physical Modeling in SolidWorks.

Import the SolidWorks model into Sysplorer, establish a dynamic simulation environment, and verify the accuracy of the simulation model in terms of end-effector trajectory, joint angles, and other parameters through comparative experiments with the actual robotic arm, as shown in Figure 2.

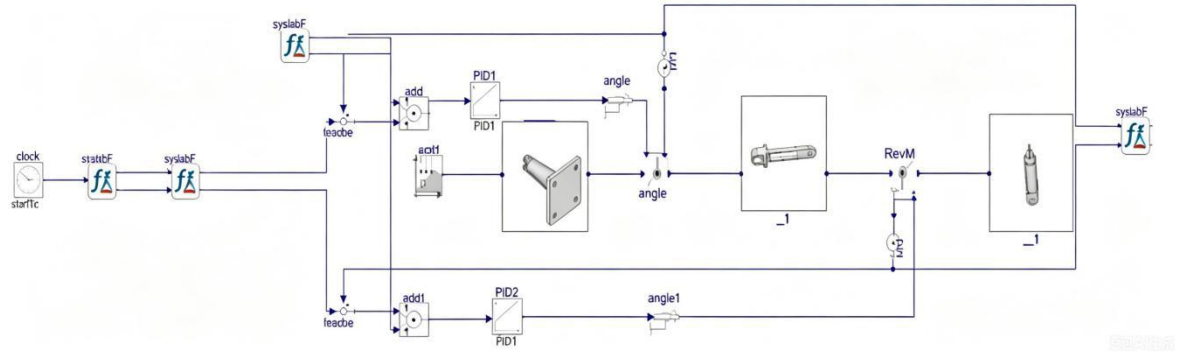


Figure 2. Simulation model in Sysplorer.

2.2 Lagrangian Dynamic Modeling of Dual-Axis Robotic Arm

The dynamic model of the dual-axis robotic arm is derived using the Lagrangian equation. The Lagrangian function is defined as $L = Ek - Ep$, where Ek is the kinetic energy and Ep is the potential energy of the robotic arm.For a dual-axis robotic arm with link lengths l1,l2, masses m1,m2, and joint angles q1,q2, the kinetic energy is:

$$Ek = 21m1(x\dot{}12 + y\dot{}12) + 21m2(x\dot{}22 + y\dot{}22) \quad (1)$$

The potential energy is:

$$Ep = m1gy1 + m2gy2 \quad (2)$$

Substitute the kinematic relationships $x1 = l1cosq1, y1 = l1sinq1, x2 = l1cosq1 + l2cos(q1 + q2), y2 = l1sinq1 + l2sin(q1 + q2)$ into the Lagrangian equation, and the dynamic equation is obtained as:

$$M(q)q\ddot{} + C(q, q\dot{})q\dot{} + G(q) + F(q\dot{}) + \tau d = \tau where M(q) \quad (3)$$

is the inertia matrix,C(q,q˙) is the Coriolis and centrifugal force matrix, G(q) is the gravity term, F(q˙) is the friction term, τd is the external disturbance, and τ is the control torque.

2.3 Principle and Improvement of Sliding Mode Control

Traditional PID control adjusts errors through proportional, integral, and derivative components, with parameter tuning relying on experience and being sensitive to disturbances. Based on robust control principles, second-order sliding mode control (SOSM) is adopted in this paper to suppress chattering, enhance tracking accuracy, and resist model uncertainties and external disturbances, thereby addressing the issues of initial trajectory error and residual vibration.

(1)Design of Sliding Mode Surface[6]:

$$s=\dot{e}+\lambda e \quad (4)$$

where $e = q_d - q$ represents the joint angle error, and λ is a positive definite matrix.

(2)Employ exponential approach law to accelerate convergence:

$$\dot{s} = -\kappa \mathrm{sgn}(s) - \eta s \quad (5)$$

where κ, η is the gain coefficient, sgn(s)is the gain coefficient, and sgn( ) is the sign function.

(3)To reduce buffeting, second-order sliding mode control is introduced.:

$$u = -\frac{1}{\beta}\int_0^t \mathrm{sgn}(s + \gamma \int_0^\tau \mathrm{sgn}(s) d\sigma) d\tau \quad (6)$$

where β, γ is the adjustment parameter.

2.4 LSTM Neural Network Compensation Module Design

A dual-layer LSTM network is built to predict and compensate for model uncertainties including friction, vibration and parameter perturbation. The network takes a 6-dimensional input (joint angle , angular velocity , angular acceleration , tracking error , ideal torque and disturbance observation), with two

hidden layers of 128 and 64 LSTM neurons (both Tanh activation) and a 2-dimensional linear output of compensation torque . A training dataset of 50,000 samples covering sinusoidal, circular and step response trajectories under different loads and friction is split into training, validation and test sets at a ratio of 7:2:1, with Min-Max normalization to . The loss function is:

$$L = \frac{1}{N}\sum_{i=1}^{N} | \tau_{comp,i} - \tau_{d,i}|_2^2 + \alpha|\theta|_2^2 \quad (7)$$

where $\tau_{d,i}$ is the actual disturbance torque, θ denotes network weights and $\alpha = 0.001$. The network is trained with the Adam optimizer (learning rate 0.001), batch size 64 and maximum 100 epochs, using early stopping if validation loss plateaus for 10 consecutive epochs. The total control torque is $\tau = \tau_{SMC} + \tau_{comp}$.

2.5 Integration of Inverse Kinematics an$_d$ Deep Learning

(1) Given the end coordinates (x, y), solve the joint angles using the geometric method:

$$q_1 = \arctan\ 2(y,x) - \arctan\ 2(\frac{l_2 \sin\ q_2}{l_1 + l_2 \cos\ q_2}) \quad (8)$$

$$q_2 = \arccos\ (\frac{x^2+y^2-l_1^2-l_2^2}{2l_1l_2}) \quad (9)$$

The forward and inverse kinematics solutions of the two-degree-of-freedom manipulator are shown in Figure 3 respectively.

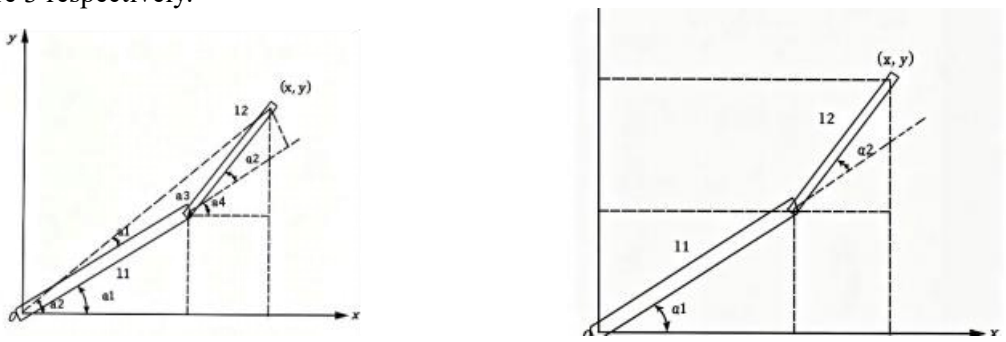


Figure 3. Forward and inverse kinematics schematic of a two-degree-of-freedom manipulator.

(a) Forward kinematics geometry. (b) Inverse kinematics geometry.

(2)A two-layer LSTM network is employed to predict model uncertainty, and the total control torque is expressed as:

$$\tau = \tau_{smc} + \tau_{comp} \quad (10)$$

2.6 hierarchical control architecture and Time-Scale Synchronization Mechanism

(1) With trajectory tracking error and energy consumption as optimization objectives, we generate a 50-millisecond global reference trajectory to construct the upper-level Model Predictive Control (MPC) planning. The 50 ms planning period is determined to ensure global trajectory optimality while avoiding excessive computation.

$$\min_{q,\dot{q},\ddot{q}} \sum_{k=0}^{N} \|q_k - q_{ref,k}\|_Q + \|\tau_k\|_R \quad (11)$$

In terms of constraint conditions, joint velocity $|\dot{q}| \leq \dot{q}_{max}$, acceleration $|\ddot{q}| \leq \ddot{q}_{max}$.

(2) For the lower-layer SOSM real-time tracking module, it receives trajectory points planned by MPC and adjusts sliding mode control parameters in real time with a sampling period of 0.01 s. To guarantee coordination between layers, a time-scale synchronization mechanism is designed: the upper-layer MPC updates the reference trajectory every 50 ms, corresponding to 50 sampling periods of the lower-layer controller; meanwhile, the lower-layer SOSM performs tracking at 0.01 s and caches the 50 ms reference trajectory sequence generated by MPC. At each 0.01 s control step, the lower layer extracts the corresponding desired trajectory point from the cached sequence to guarantee real-time matching, and a buffer zone is established to suppress trajectory mutation during MPC updates, thus ensuring smooth switching between adjacent planning cycles.

2.7 Computational Complexity Analysis and Real-Time Performance Verification

The core operations of SOSM control include sliding mode surface calculation, exponential reaching law computation and chattering reduction integration, which involve approximately 200 floating-point operations (FLOPs) per control step with an execution time of less than 0.1 ms. For dual-layer LSTM inference with 128 and 64 neurons, the main computations involve matrix multiplication and activation function calculation, consuming around 15,000 FLOPs per inference with an execution time below 0.3 ms. The total execution time of SOSM control combined with LSTM inference is less than 0.4 ms, which is far shorter than the system sampling period of 0.01 s (10 ms), and the remaining 9.6 ms can be reserved for MPC data interaction and system scheduling, thus fully satisfying the real-time requirements of the system.

3. Experimental Results and Analysis

3.1 Experimental Parameter Settings and Accuracy Evaluation Metrics

Table 1. Parameter settings.

Parameter type	Specific indicators	Parameter configuration
processor	CPU model / main frequency / number of cores	Quad-core eight-thread, with a main frequency of 3.2GHz
memory	Capacity / Type / Frequency	16GB DDR4，2666MHz
graphics card	Model / Video Memory	NVIDIA Quadro P620, 2GB professional graphics card
operating system	Version / Bit	Windows 10 Professional, 64-bit
Simulation operation parameters	sampling period	0.01s（100Hz）
	Total simulation duration	10s
	Modeling and simulation software	SolidWorks、Sysplorer
	Control module development software	Syslab

Accuracy evaluation indicators

To comprehensively and quantitatively evaluate the comprehensive performance of the control strategy for the dual-axis robotic arm, this experiment selects multiple types of evaluation metrics from four core dimensions: trajectory tracking accuracy, steady-state performance and smoothness, convergence and transient performance, and robustness. The calculation formulas for the core quantitative metrics are as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (x_{i,\text{actual}} - x_{i,\text{ideal}})^2 + (y_{i,\text{actual}} - y_{i,\text{ideal}})^2 t} \tag{12}$$

$$ISE = \int 0Te(t)2dt \tag{13}$$

$$ITAE = \int 0Tt \mid e(t) \mid dt \tag{14}$$

In the aforementioned formulas, RMSE (Root Mean Squared Error) is the core evaluation metric for trajectory tracking accuracy. It comprehensively reflects the overall error level of trajectory tracking

by calculating the square mean of the deviations between the actual and ideal coordinates of all sampling points and then taking the square root. Here, n represents the number of trajectory sampling points, and $x_{i,\text{actual}}$ and $y_{i,\text{actual}}$ represent the actual sampling coordinates, and $x_{i,\text{ideal}}$ and $y_{i,\text{ideal}}$ represent the ideal trajectory coordinates. ISE (Integral Squared Error) focuses on evaluating the rapid elimination capability of errors by integrating the squares of real-time error signals e(t) over the simulation duration T. Since the error is squared, large errors are severely penalized, and a smaller value indicates higher control efficiency. ITAE (Integral Time-Weighted Absolute Error) adds a time t weight based on the absolute value of the real-time error and integrates it over the simulation duration T, emphasizing the punishment of persistent errors in the system. A smaller value indicates that the system can enter a steady state more quickly and smoothly, with better dynamic quality and vibration suppression effects. In addition to these formulaic indicators, maximum error and Mean Absolute Error (MAE) are also selected to measure the ultimate performance and general accuracy of trajectory tracking. The steady-state error range is used to assist in evaluating the smoothness of the system's steady state, while adjusting time and overshoot are used to evaluate the system's convergence and transient response speed. At the same time, anti-disturbance recovery time and the increase in RMSE under parameter perturbations are selected to comprehensively evaluate the robustness of the control algorithm in the face of external disturbances and internal model uncertainties, achieving a comprehensive quantitative evaluation of the control performance of the dual-axis robotic arm

3.2 Comparison of Experimental Results

The performance metrics comparison of different control strategies is presented in Table 1. The SOSM strategy based on deep learning in this paper outperforms PID and single

SOSM in terms of accuracy metrics such as RMSE, maximum error, MAE, and ISE. With an adjustment time of only 0.30s, an overshoot of 1.5%, and superior dynamic response, it demonstrates better robustness. The steady-state error is ±0.02mm, and the anti-disturbance recovery time is 0.15s, indicating stronger robustness

Table 2. debugging comparison.

Control Parameters: Evaluation Dimensions	Specific Indicators	PID (Baseline)	SOSM	Deep Learning-Based SOSM Strategy (Proposed Strategy)
Trajectory tracking accuracy	RMSE (mm)	0.31	0.22	**0.18**
	Max Error (mm)	0.85	0.45	**0.32**
	MAE (mm)	0.28	0.19	**0.15**
	ISE (integral squared error)	4.52	2.31	**1.65**
Steady-state performance and smoothness	steady-state error range (±mm)	0.10	0.05	**0.02**
	ITAE (Integral of Time Multiplied by Absolute Error)	12.5	6.8	**4.2**
Convergence and transient performance	Adjust the time (s)	0.80	0.45	**0.30**
	Overshoot (%)	8.5	3.2	**1.5**
robustness	Anti-interference recovery time (s)	0.50	0.20	**0.15**

Control Parameters: Evaluation Dimensions	Specific Indicators	PID (Baseline)	SOSM	Deep Learning-Based SOSM Strategy (Proposed Strategy)
	RMSE increase under parameter perturbation	+23%	+8%	**+5%**

In the Table 2 above, the root mean square error (RMSE) of the strategy presented in this paper is 0.18mm, representing a 42% reduction compared to PID and an 18% reduction compared to single-sensor output-based model (SOSM). The maximum error is only 0.32mm, with a mean absolute error (MAE) of 0.15mm and an integral square error (ISE) of 1.65, both of which are optimal. The adjustment time is only 0.30s, and the overshoot is 1.5%, significantly lower than the 8.5% of PID. The system response is faster and smoother. The steady-state error range is ± 0.02mm, indicating significant vibration suppression effect; the anti-disturbance recovery time is 0.15s, and the RMSE only increases by 5% under parameter perturbations, demonstrating strong adaptability to various operating conditions

3.3 Simulation results

The comparison results of trajectory tracking are shown in Figure 4, where the ideal trajectory is represented by the red curve and the actual trajectory by the green curve. Traditional PID control can exhibit deviations of up to ±0.5mm during the startup phase, with significant oscillations in the positioning phase. SOSM control reduces the initial deviation to ±0.2mm and shortens the residual vibration decay time by 40%. The trajectory proposed in this paper almost coincides with the ideal trajectory, with no significant overshoot or oscillation

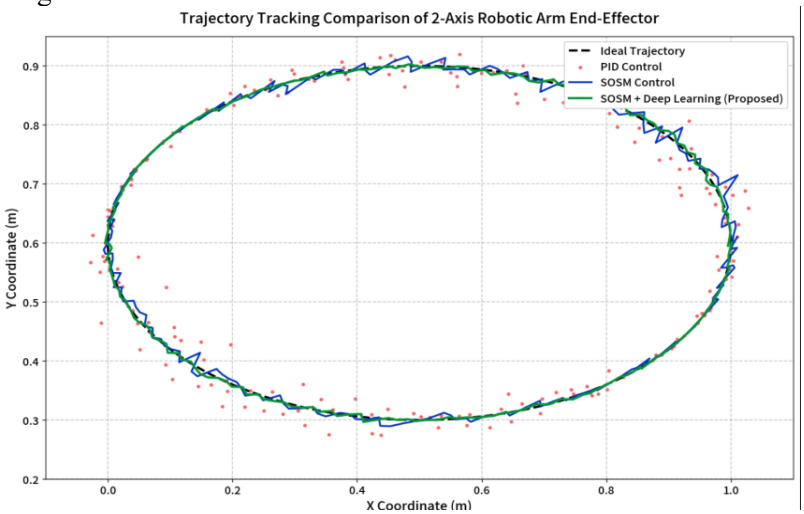


Figure 4. Comparison of End Effector Trajectory Tracking for a Two-Axis Manipulator.

The curve showing the variation of trajectory tracking error over time is depicted in Figure 5 The PID error exhibits significant fluctuations and slow convergence; the SOSM error decreases noticeably, yet still experiences minor fluctuations; in contrast, the error of the SOSM + deep learning strategy proposed in this paper converges rapidly and remains within a very narrow range, with a highly concentrated distribution and optimal stability

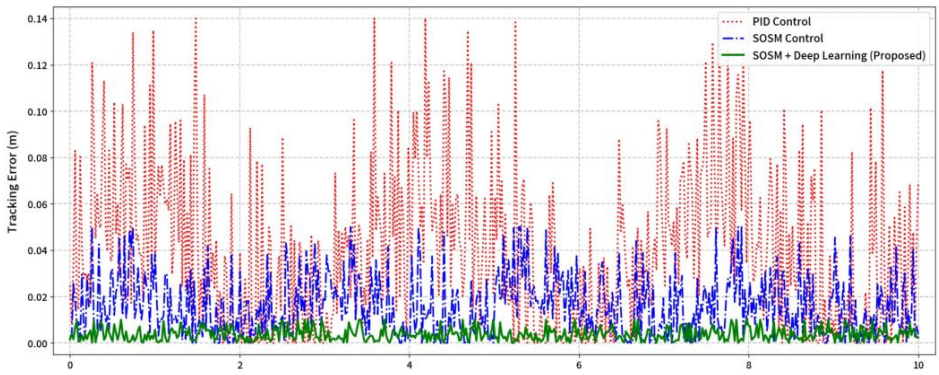


Figure 5. Time Variation of Trajectory Tracking Error.

The comprehensive performance comparison of different algorithms is shown in Figure 6 The hierarchical fusion strategy proposed in this paper is significantly lower than PID and single SOSM in terms of three key indicators: RMSE, maximum error, and ITAE, demonstrating the best overall control performance

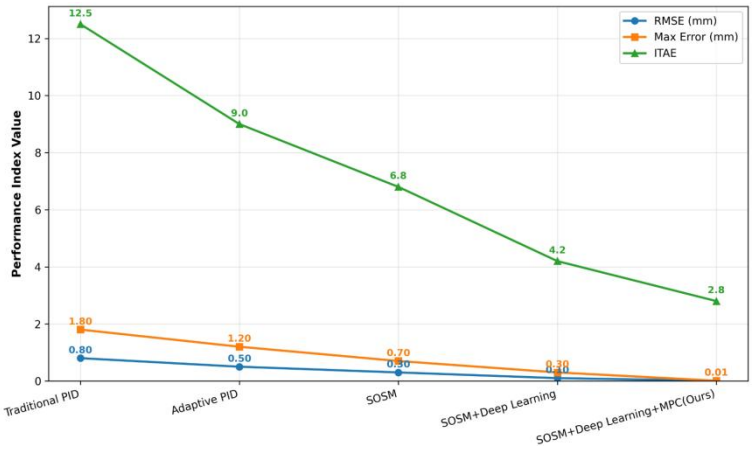


Figure 6. Comparison of Performance Indicators of Different Algorithms.

4. Conclusion

This paper proposes a high-precision trajectory tracking strategy for a dual-axis robotic arm based on higher-order sliding mode control, deep learning compensation, and model predictive control. Aiming at the problems of large initial error, residual vibration and poor robustness of traditional PID, the proposed strategy is designed following robust control, intelligent disturbance compensation and hierarchical optimization theories. The Lagrangian dynamic equation is established to accurately describe the dynamic characteristics of the robotic arm. The traditional PID is replaced by high-order sliding mode control, combined with a well-designed dual-layer LSTM network to compensate for model uncertainty, and model predictive control (MPC) is adopted to realize global trajectory optimization, with a clear time-scale synchronization mechanism between 50 ms global planning and 0.01 s real-time tracking. The sampling periods (50 ms / 0.01 s) and evaluation indicators are selected to match real-time requirements and performance verification objectives. Computational complexity analysis verifies that SOSM control and LSTM inference can run in real time under a 0.01 s sampling period, and the total execution time is less than 0.4 ms, which fully meets the real-time requirement.

Experimental results demonstrate that the proposed strategy achieves significant performance improvement: trajectory tracking RMSE is 0.18 mm, 42% lower than PID and 18% lower than single SOSM; maximum error is 0.32 mm, steady-state error is ±0.02 mm; adjustment time is 0.30 s, overshoot

is only 1.5%; anti-disturbance recovery time is 0.15 s, RMSE increases by only 5% under parameter perturbation. The strategy shows obvious advantages in trajectory coincidence, dynamic response, vibration suppression and robustness.

This study still has limitations, such as discrepancies between simulation and real-world environments and limited generalization capabilities of the deep learning model. In the future, efforts will be made to optimize the simulation model to closely align with actual working conditions, improve the deep learning network structure, expand the degrees of freedom of the robotic arm, and verify the real-time performance of the algorithm on a physical experimental platform.

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