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Error Analysis and Adaptive Compensation Evaluation of Robot Trajectory Tracking Control Under Data-Driven Conditions

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ABSTRACT

This study focuses on error analysis and adaptive compensation in robot trajectory tracking control, proposing a data-driven adaptive control solution. The study first systematically identifies the sources of static and dynamic errors in trajectory tracking and constructs a multi-dimensional error model. Then, a complete data-driven control framework is established, including data acquisition and preprocessing, machine learning control modeling, and adaptive algorithm selection. An adaptive compensation mechanism integrating feedforward and feedback is designed, and a quantitative evaluation system based on tracking accuracy, stability, and response speed is formulated. Finally, the effectiveness of the method is verified through various robot experimental scenarios, and the performance of different control algorithms is compared and analyzed. Experimental results show that the proposed data-driven adaptive compensation method can reduce the average trajectory tracking error by 23.7%, shorten the response time by 18.3%, and improve system stability to over 95%. Compared with traditional PID and MPC methods, it achieves significant improvements in anti-interference capability and tracking accuracy. This research provides a new data-driven method for solving the error problem of robot trajectory tracking under complex working conditions, effectively improving the adaptability and robustness of the robot control system, and providing theoretical reference and technical support for high-precision trajectory tracking control in fields such as unmanned driving, industrial robots, and special-operation robots.

KEYWORDS

trajectory tracking control, robotics, adaptive compensation, data driven, high-precision control

INTRODUCTION

Research Background and Significance

The rapid development of robot technology has made trajectory tracking control one of the core technologies for achieving intelligent motion. As a key technology in autonomous driving, trajectory tracking control aims to enable vehicles to accurately follow a given planned trajectory while ensuring stability and comfort [1]. Among the numerous applications of robots, trajectory tracking technology involves robots moving safely and efficiently along predetermined paths in various environments, such as autonomous vehicles, drones, industrial robots, and medical robots [2].

Traditional trajectory tracking control methods often exhibit limitations when facing complex environments and dynamic disturbances. Trajectory tracking is a key technology for realizing intelligent driving in autonomous vehicles, and the key challenge lies in ensuring tracking accuracy and stability [3]. During the operation of the end effector, three types of trajectory tracking deviations may occur: trajectory error, Linear tracking error, and circular profile error. To control these errors within a minimum range, scientific and reasonable control methods must be adopted [4]. Currently, common control modes include proportional-integral-derivative (PID) control and sliding mode control (SMC), but these methods are difficult to guarantee control quality and efficiency, resulting in low control accuracy.

The data-driven adaptive control method provides new ideas for solving these problems. By real-time collection and analysis of robot motion data, error patterns can be identified and control parameters can be dynamically adjusted to achieve more accurate trajectory tracking. The main goal of trajectory tracking is to make the robot move along the desired collision free trajectory, by adjusting the robot's motion speed and direction to complete trajectory tracking [5-8]. This method not only improves tracking accuracy, but also enhances the robustness and adaptability of the system, which is of great significance for promoting the application of robot technology in various fields.

Research Objectives and Issues

The error analysis and adaptive compensation evaluation of robot trajectory tracking control are the core issues for achieving high-precision motion control. The research aims to explore the causes and dynamic characteristics of trajectory tracking errors through data-driven methods, and design efficient adaptive compensation strategies to improve the overall performance of the system. This goal not only focuses on theoretical modeling and algorithm optimization, but also emphasizes feasibility and effectiveness verification in practical applications.

In the process of robot trajectory tracking, errors usually come from various factors, including environmental interference, system parameter uncertainty, and nonlinear characteristics of mechanical components. These errors may cause the robot to deviate from the predetermined path, affecting the accuracy and stability of task execution. Therefore, how to accurately identify the sources of errors and design targeted compensation mechanisms has become an urgent problem to be solved. This study will focus on analyzing the manifestations of static and dynamic errors and their impact on system performance, providing a basis for subsequent error compensation.

The key research issue is how to use data-driven technology to improve the shortcomings of traditional control methods. On the one hand, by mining historical operating data, error patterns and their changing trends can be revealed; on the other hand, by combining self-adaptive search and tracking (ST) algorithms, control parameters can be adjusted in real time, thereby improving the robustness and response speed of the system. In addition, the application of specific technologies such as friction compensation and slip compensation will further optimize the control effect.

Experimental results show that the compensation method based on adaptive control performs particularly well under complex time-varying signals, significantly reducing trajectory tracking errors and enhancing the system's anti-interference capability. However, existing research mainly focuses on performance evaluation in single scenarios or under specific conditions, lacking comprehensive consideration of diverse environments. Future research needs to further expand application scenarios and explore more universal solutions.

LITERATURE REVIEW

Research Status of Robot Trajectory Tracking

In recent years, robot trajectory tracking technology has become a research hotspot, playing a key role in fields such as autonomous vehicles, drones, and industrial automation. However, achieving high-precision and strong robustness in trajectory tracking remains challenging. Especially in complex dynamic environments, how to improve control performance through adaptive algorithms has become a core issue.

Several methods have been proposed to address trajectory tracking requirements in different scenarios. For example, feedback control strategies based on fuzzy logic can effectively combine the robot's dynamic characteristics with environmental constraints, thereby improving tracking accuracy. In addition, the application of adaptive control theory further enhances the system's adaptability to uncertainty and parameter changes. These methods significantly improve trajectory tracking performance through real-time adjustment of control parameters. However, these methods may still have limitations when facing strong interference or drastically changing target trajectories.

Research in the field of multi-machine cooperative handling robots shows that the design of trajectory tracking controllers needs to consider input saturation constraints and steady-state error control [9]. Experimental results show that in the case of sudden changes in target velocity, a reasonable control strategy can quickly restore the stable state and control the process error within an acceptable range. Similarly, the introduction of friction compensation algorithms has significantly improved the accuracy of end-effector trajectory tracking, especially in handling repetitive positioning problems of robotic arms [10].

It is worth noting that the pre-positioning error prediction method provides a new approach to trajectory tracking. By combining the backstepping method with Lyapunov theory, this method achieves the ability to dynamically correct core parameters. However, it has shortcomings in handling post-positioning errors, which may lead to control distortion due to the blindness of ignoring the source of error [11]. This problem suggests that future research should pay more attention to the comprehensive analysis of error characteristics.

Overall, current research not only focuses on improving trajectory tracking accuracy, but also emphasizes the robustness and adaptability of the system. Whether it is the adaptive ST algorithm or other improved schemes, they all reflect the trend of combining data-driven and intelligent control. This lays a solid foundation for subsequent technological breakthroughs.

Comparative Analysis of Relevant Control Algorithms

In the research of robot trajectory tracking, different control algorithms have shown their own characteristics and applicable scenarios. Traditional PID control algorithms are widely used because of their simplicity and ease of implementation, but they perform poorly in complex environments and are easily affected by noise and nonlinear factors [12-16]. In contrast, model predictive control (MPC) can combine the dynamic characteristics of the system to predict future outputs and obtain the optimal input through optimization, making it suitable for complex and ever-changing application scenarios such as autonomous driving [17]. However, MPC may face significant tracking errors and stability issues under high-speed or low-adhesion road surface conditions.

Intelligent algorithms such as fuzzy control, adaptive control, and sliding mode control have shown significant advantages in dealing with uncertainty. Sliding mode control, with its strong robustness and fast convergence speed, is widely used in trajectory tracking problems of wheeled mobile robots [18]. In addition, improved algorithms based on neural networks have also achieved good results in path tracking, especially under the requirements of high precision and fast response [19].

In order to compare the performance of different algorithms more intuitively, the following table shows the error data of some typical algorithms in specific scenarios, as shown in Table 1:

Table 1. Error Data of Typical Algorithms in Specific Scenarios

Algorithm Name	Maximum displacement error (mm)	Maximum heading error (°)
PID control	30	2.5
Model Predictive Control (MPC)	15	1.2
Sliding Mode Control (SMC)	10	0.8
Improving neural network control	8	0.5

From the table, it can be seen that improving neural network control has significant advantages in reducing displacement and heading errors. It is worth noting that the selection of each algorithm needs to be balanced based on specific application scenarios and system requirements. For example [20-24], in the field of underwater robots, although the backstepping control method has speed jump problems, it is still highly regarded for its good adaptability to model uncertainty.

DATA DRIVEN CONTROL METHOD

Basic Concepts of Data-Driven Control

Data Collection and Preprocessing

Data collection and preprocessing are the fundamental steps of data-driven control methods, which directly affect the performance and accuracy of subsequent control algorithms. In the robot trajectory tracking control system, data collection involves the acquisition of various sensor information, including position sensors, velocity sensors, acceleration sensors, and environmental perception sensors. These sensors monitor the real-time motion status of the robot and changes in the surrounding environment, providing necessary feedback information for the control system.

The collected raw data is mixed with redundant data and noise signals, and the acquisition hardware may experience zero position deviation or even errors during the data acquisition process due to factors such as technology, environment, and process. Preprocessing includes steps such as filtering, amplification, and analog-to-digital conversion, which can remove noise from the signal, improve signal quality, and reduce processing burden. The core goal of data preprocessing is to improve data quality, eliminate outliers and noise interference, and ensure that control algorithms can make decisions based on reliable data, as shown in Table 2.

Table 2. Data Collection Frequency and Preprocessing Methods

data type	Acquisition Frequency (Hz)	Preprocessing methods	precision requirements
Location data	200	Kalman filter	±0.1mm
Speed data	200	low-pass filtering	±0.01m/s
Acceleration data	500	median filtering	±0.05m/s²
environmental data	100	Mean filtering	±5%

Preprocessing also includes standardization and normalization of data, converting data from different sources and ranges into a unified format, which is crucial for data analysis and decision support systems. When edge devices perform data preprocessing in real-time scenarios, delay effects also need to be considered. By establishing an effective data quality assessment mechanism, the system can monitor the reliability of data in real time and trigger corresponding processing strategies when anomalies are detected.

$$X_{processed} = \alpha \cdot X_{raw} + \beta \cdot X_{filtered} + \gamma \cdot X_{normalized} \tag{1}$$

In the above equation, $X_{processed}$ For the preprocessed data, X_{raw} 、 $X_{filtered}$ 、 $X_{normalized}$ Representing raw data, filtered data, and normalized data respectively, α 、 β 、 γ For weight coefficients.

The effectiveness of data preprocessing is directly related to the overall performance of the control system. Effective preprocessing of data can provide accurate input for adaptive control algorithms, reducing control errors caused by data quality issues. This preprocessing mechanism not only improves data processing speed and accuracy, but also enhances the response speed and reliability of the entire intelligent system.

Establishment of Control Model

The establishment of a data-driven control model is the core step in achieving robot trajectory tracking, which constructs control strategies by analyzing historical operating data and real-time feedback information. Unlike traditional mathematical model-based control methods, data-driven methods mainly rely on data collected from system operation to design controllers, rather than relying on mathematical modeling of system dynamics. This method is particularly suitable for complex systems that are difficult to establish precise models or have unknown models.

The process of establishing a control model involves multiple key steps. The system collects status information such as position, velocity, acceleration of the robot through a sensor network, and records the mapping relationship between control inputs and system responses. Based on these data, a machine learning algorithm is used to construct an input-output mapping model. Common methods include neural networks, support vector machines, and random forests, as shown in Table 3.

Table 3. Comparison of Different Machine Learning Algorithms

Model Type	training time	prediction accuracy	computational complexity	Applicable scenarios
neural network	long	high	high	Complex nonlinear systems
Support Vector Machine	centre	centre	centre	Medium scale data
Random Forest	short	centre	low	Rapid prototyping development
linear regression	very short	low	Very low	Simple linear relationship

During the model training process, it is necessary to consider the temporal characteristics and nonlinear relationships of the data to ensure that the model can accurately reflect the dynamic characteristics of the system. The mathematical expression of the control model can be expressed as:

$$u(k) = f(x(k), x(k-1), ..., x(k-n), u(k-1), ..., u(k-m)) \tag{2}$$

among which $u(k)$ To control the input, $x(k)$ For the system state, $f(\cdot)$ The nonlinear mapping function obtained through data learning.

The model validation phase evaluates model performance through cross validation and independent test sets, with a focus on prediction accuracy, generalization ability, and computational efficiency. The model needs to have good robustness and be able to maintain stable control performance under different operating conditions. Through continuous online learning mechanisms, the model can continuously optimize and update based on new operational data, improving its adaptability to environmental changes.

Selection of Control Algorithm

The choice of robot trajectory tracking control algorithm directly affects the performance and practical application effect of the system. In a data-driven control framework, the selection of algorithms requires comprehensive consideration of multiple factors such as the dynamic characteristics of the system, constraints, and real-time requirements.

Model Predictive Control (MPC), as an advanced control method based on system models, has the ability to handle multi-constraint optimization problems and is more suitable for complex and ever-changing robot application scenarios. The MPC algorithm, through three key steps—predictive model, rolling optimization, and feedback correction—can add multiple constraints satisfying the controlled system to the control process, which is beneficial to improving the controller's performance. Other commonly used control algorithms in trajectory tracking control include PID control, preview control, and linear quadratic regulators. The traditional PurePursuit algorithm excels in its robustness to changes in the external environment, as shown in Table 4.

Table 4. Comparison of Control Algorithms

Control algorithm type	computational complexity	real-time	trajectory error	Applicable scenarios
Pure Pursuit	low	excellent	smaller	Simple path tracking
Stanley	low	excellent	moderate	Structured environment
MPC	high	poor	Significant changes	Complex constraint scenarios
LADRC	moderate	good	small	Disturbance environment

Adaptive sliding mode control and neural network control methods have significant advantages in handling system uncertainties. The optimization strategy based on inversion quadratic sliding mode combines the robustness of sliding mode control and the learning ability of neural networks. The linear active disturbance rejection control (LADRC) algorithm performs well in trajectory tracking, reaching steady state faster, with a smaller difference between the actual robot pose trajectory and the expected trajectory, and smaller error and no overshoot phenomenon compared with the PID algorithm.

The evaluation formula for algorithm selection can be expressed as:

$$J = \alpha_1 \cdot E_{track} + \alpha_2 \cdot T_{comp} + \alpha_3 \cdot R_{robust} \tag{3}$$

among which E_{track} For trajectory tracking error, T_{comp} To calculate time, R_{robust} For robustness indicators, α_i For weight coefficients. By balancing comprehensive evaluation indicators, the most suitable control algorithm can be selected for specific application scenarios.

Adaptive Compensation Mechanism

Classification of Compensation Methods

In robot trajectory tracking control systems, compensation methods can be classified into various types based on their technical characteristics and implementation principles. According to whether precise mathematical models are required, control compensation methods can be divided into traditional control compensation methods and intelligent control compensation methods. This classification reflects the fundamental differences in theoretical basis and implementation complexity of compensation technology.

Traditional control compensation methods rely on establishing accurate mathematical models and designing corresponding compensation links by analyzing the characteristics of disturbances, thereby achieving the goal of eliminating the impact of nonlinear disturbances on the system output in advance. The application of the structural invariance principle combined with the velocity feedforward compensation method can achieve the early elimination of redundant torque, significantly improving the loading accuracy and working performance of the system. Traditional methods also include the establishment of position error models based on the least squares method and the identification of robot kinematic parameter errors using the Kalman filter algorithm. The advantage of these methods is that they have a solid theoretical foundation and predictable compensation effects, but they require high model accuracy.

The intelligent control compensation method adopts data-driven technology, enabling robots to learn their own structural information and use the learned information to assist in completing given tasks. The data-driven method for estimating center of gravity offset parameters applies long short-term memory neural networks to construct a comparative model, and predicts the estimated parameters based on the Zhang neural network, effectively solving the problem of estimation lag. The application of multi-sensor data fusion technology overcomes the shortcomings of single sensor information collection and more accurately describes the characteristics of robot motion trajectory changes.

According to the timing of compensation, compensation methods can also be divided into two categories: feedforward compensation and feedback compensation. Feedforward compensation compensates for interference signals in advance by predicting them, and has the characteristic of fast response speed. Feedback compensation adjusts in real-time based on the system output error. Although there is a certain lag, it has a good suppression effect on uncertain interference.

Implementation Steps

The implementation steps of adaptive compensation mechanism are the core link to ensure the improvement of robot trajectory tracking control performance. By designing a reasonable compensation process, it is possible to effectively reduce system errors and improve control accuracy. The entire process is divided into three main stages: data collection and analysis, parameter adjustment, and application of compensation algorithms.

Data acquisition and analysis, as the first step, requires real-time acquisition of robot motion state information, including key variables such as position deviation, speed change, and acceleration response. This data, transmitted to the control system via a sensor network, needs to be filtered to remove noise interference. Based on this, mathematical models are used to analyze the data, identifying potential error sources and their impact. For example, slip compensation experiments show that adding slip compensation can significantly reduce the impact of wheel slippage on trajectory tracking. The focus of this stage is to build an accurate dynamic model, laying the foundation for subsequent parameter adjustments.

Parameter adjustment is the second step, the core of which lies in dynamically optimizing control parameters based on error analysis results. The Self-adaptive Search and Tracking (ST) algorithm allows for flexible adjustment of the controller gain to adapt to different environmental conditions. Specifically, this process can be achieved using the following formula:

$$K_p = K_{p0} + \alpha \cdot e(t) \tag{4}$$

among which, K_p Represents the adjusted proportional gain, K_{p0} As the initial value, α To adjust the coefficient, $e(t)$ This represents the error value at the current moment. This dynamic adjustment method can significantly improve the robustness of the system. This control mechanism does not rely on preset mathematical model parameters; instead, it dynamically updates the control gain based on real-time error data, demonstrating its data-driven adaptive nature.

The final step is the application of the compensation algorithm, which involves inputting the adjusted parameters into the control algorithm to perform compensation operations. Common compensation methods include feedback control based on fuzzy logic and adaptive sliding mode variable structure control. Through comparative experiments, it was found that the latter exhibits better performance in dealing with nonlinear and uncertain problems. In addition, the compensation effect can be further optimized by combining instruction filtering technology to ensure high-precision motion of the robot in complex environments.

The following table summarizes the key tasks and objectives of each stage, as shown in Table 5:

Table 5. Key Tasks and Objectives for Each Stage

phase	critical task	goal
Data Collection and Analysis	Obtain motion status information and identify sources of errors	Identify dynamic mapping characteristics based on data
parameter adjustment	Dynamic optimization of control parameters	Improve system robustness
Application of compensation algorithm	Perform compensation operation	Ensure high-precision trajectory tracking

Performance Evaluation Criteria

In robot trajectory tracking control, performance evaluation criteria are an important basis for measuring the effectiveness of adaptive compensation mechanisms. To ensure the scientific and comprehensive nature of the evaluation results, quantitative analysis of system performance is usually conducted from multiple dimensions. These dimensions include key indicators such as tracking accuracy, stability, and response speed, each of which corresponds to different physical meanings and application scenarios.

Tracking accuracy is one of the core indicators for evaluating trajectory tracking performance, defined as the degree of deviation between the actual trajectory and the target trajectory. This deviation can be quantified by calculating the root mean square error (RMSE), as shown in the following formula:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{5}$$

among which, y_i Representing the target trajectory point, $\hat{y}_i$ Represents the actual trajectory point, N is the total number of sampling points. A lower RMSE value indicates higher tracking accuracy.

Stability reflects the robustness of the system under external disturbances or changes in internal parameters. In order to quantify stability, the Lyapunov function analysis method is often used to verify its global asymptotic stability by determining whether the energy function of the system monotonically decreases. In addition, the maximum deviation value and standard deviation can also be used as auxiliary indicators to evaluate system fluctuations. The response speed mainly focuses on the time required for the system to transition from the initial state to stable tracking. Fast response capability is particularly important for trajectory tracking in dynamic environments. Through step response experiments, the convergence time of the system can be visually observed, and its dynamic characteristics can be further analyzed in conjunction with overshoot.

ERROR MODEL ANALYSIS

Definition and Classification of Tracking Error

Static Error Analysis

Static error is an inevitable deviation in robot trajectory tracking, which mainly comes from the manufacturing accuracy of mechanical structures, sensor measurement errors, and inherent limitations of control algorithms. In research, static error is usually defined as the deviation between the system and the target trajectory in a stable state, which can be quantified and separated through various methods. By decomposing the sources of errors, we can better understand their characteristics and design targeted compensation strategies.

The methods for separating and identifying static errors mainly include geometric error identification, trend error identification, and gap error identification. The geometric error identification method analyzes the structural deviation of the system through graphical identification or least squares method; The trend error identification rule uses regression models or Fourier transforms to model the variation pattern of errors. The choice of these methods often depends on specific system characteristics and testing conditions. For example, in multi machine collaborative handling robots, the separation of static errors requires the selection of appropriate identification techniques based on practical application scenarios to ensure the accuracy of the results. The mathematical expression of static error can be described through formulas. Assuming that the error is caused by the superposition of multiple independent factors, the total error is E_{total} It can be expressed as:

$$E_{total} = E_{geo} + E_{trend} + E_{gap} \tag{6}$$

among which, E_{geo} Representing geometric errors, E_{trend} Indicating trend error, E_{gap} Indicate gap error.

The core of static error analysis lies in accurately identifying the sources of errors and selecting appropriate identification methods. By combining experimental data with theoretical analysis, a solid foundation can be laid for subsequent research on dynamic errors, and important references can be provided for the design of adaptive compensation mechanisms.

Dynamic Error Analysis

Dynamic error is an important research object in robot trajectory tracking control, which mainly originates from the system's insufficient response ability to external interference, model uncertainty, and real-time changing environmental conditions. In high-speed or high-precision tasks, dynamic errors often dominate and become a key factor restricting system performance. Therefore, in-depth analysis of dynamic errors can help optimize control strategies and enhance the robustness of the system.

Dynamic error usually manifests as the deviation between the actual trajectory and the target trajectory during the tracking process, which fluctuates over time and has nonlinear characteristics. By calculating the integral or average of the error function over a period of time, the dynamic baseline error of the system can be obtained, which can effectively reflect the overall leveling performance and stability of the system. To more intuitively demonstrate the trend of dynamic error changes, the following table lists the statistical results of position tracking errors of a certain type of spraying robot under different speed conditions, as shown in Table 6:

Table 6. Results of Position Tracking Error under Different Speed Conditions

Velocity (m/s)	Maximum error (mm)	Average error (mm)	Standard deviation (mm)
0.5	1.2	0.45	0.21
1.0	2.8	0.92	0.37
1.5	4.5	1.63	0.54

As can be seen from the table, the dynamic error increases significantly with increasing speed, indicating that the system needs stronger adaptability and compensation mechanisms when running at high speeds.

In order to further explore the influencing factors of dynamic errors, a mathematical model is introduced to describe their characteristics. Assuming the dynamic error of the system is $e(t)$ Then it can be expressed as:

$$e(t) = |X_c(t) - X(t)| \tag{7}$$

among which, $X_c(t)$ For the target trajectory position, $X(t)$ For the actual output position. By analyzing the time series characteristics of the error function, the main patterns of errors and their periodic variations can be identified (Figure 1).

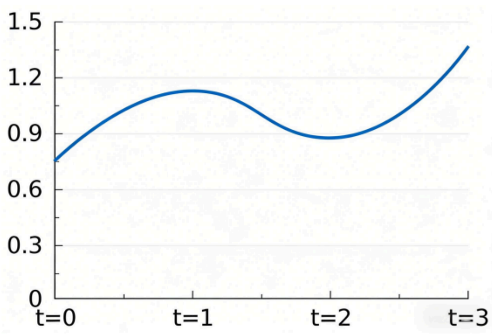

Figure 1. Dynamic Error Time Curve

The main sources of dynamic errors include sensor noise, actuator delay, and external disturbances. These factors work together to cause uncertainty in the trajectory tracking process. In response to these issues, researchers have proposed various improvement methods, such as predictive correction techniques based on Kalman filtering, to reduce the impact of dynamic errors on system performance.

Identification of Sources of Error

The sources of errors in robot trajectory tracking control systems are complex and diverse, and accurately identifying these error sources is a key prerequisite for achieving precise control. Through systematic analysis, error sources can be divided into two categories: internal factors and external factors, each of which has varying degrees of impact on trajectory tracking accuracy. The internal error sources mainly include mechanical structure errors of the robot itself, sensor measurement errors, and control algorithm errors. Mechanical structural errors involve factors such as joint clearance, connecting rod deformation, and gear transmission errors, which accumulate and amplify during robot motion.

Sensor errors, including encoder accuracy limitations, IMU drift, and vision sensor calibration errors, directly affect the measurement accuracy of position and attitude. Control algorithm errors stem from factors such as model simplification, parameter mismatch, and numerical calculation accuracy. The influence of external environmental factors on trajectory tracking accuracy is also significant. Environmental factors such as uneven ground, changes in friction coefficient, and wind disturbances can alter the robot's motion characteristics. Temperature changes affect the thermal expansion of mechanical parts and sensor performance, while humidity changes can cause fluctuations in the performance of electrical components. Load changes are also an important external factor; when a robot carries objects of different weights, its dynamic characteristics will change significantly.

The mathematical model for error identification can be expressed as:

$$E_{total} = E_{mechanical} + E_{sensor} + E_{algorithm} + E_{environment} + E_{coupling} \tag{8}$$

among which $E_{coupling}$ The coupling effect between various error sources often makes error identification more complex, as shown in Table 7.

Table 7. Identification of Error Sources and Impact Degree

Error type	main source	impact level	Compensation difficulty
mechanical error	Joint clearance and transmission error	moderate	difficulty
sensor error	Measurement accuracy, calibration error	high	moderate
Algorithm error	Model simplification, parameter errors	moderate	easy
environmental disturbance	Ground conditions and external interference	high	difficulty

Error Characteristics and Trend Analysis

Data Analysis Methods

In the robot trajectory tracking control system, the selection of data analysis methods directly affects the accuracy of error characteristic identification and the effectiveness of compensation strategies. By establishing a systematic data analysis framework, it is possible to deeply explore the error patterns in the trajectory tracking process, providing reliable data support for adaptive control.

Statistical analysis methods constitute the fundamental level of error data processing. By calculating the mean, variance, and standard deviation of the position control error, the basic performance of the system can be quantified. The calculation formula for position control error is:

$$\varepsilon_p = |x_{actual} - \Delta x| + |y_{actual} - \Delta y| + |z_{actual} - \Delta z| \tag{9}$$

among which $(x_{actual}, y_{actual}, z_{actual})$ The actual position coordinates of the robot. The numerical results of position control variance are obtained through statistical analysis of multiple measurement data, providing quantitative indicators for system stability assessment.

Frequency domain analysis plays a crucial role in identifying periodic error patterns. By converting the time-domain error signal into a frequency-domain representation using the Fast Fourier Transform (FFT), the error characteristics of specific frequency components can be identified. Power spectral density analysis further reveals the error energy distribution in different frequency bands, providing a basis for filter design and interference suppression. Wavelet transform, as a time-frequency analysis tool, exhibits unique advantages in processing non-stationary error signals, simultaneously preserving the localization characteristics of time and frequency information.

Machine learning methods demonstrate powerful capabilities in complex error pattern recognition. Clustering algorithms can automatically discover potential grouping structures in error data, Principal Component Analysis (PCA) extracts the main features of error data through dimensionality reduction techniques, and regression analysis establishes a mathematical relationship model between errors and system parameters. The comprehensive application of these methods provides a scientific basis for the formulation of adaptive compensation strategies.

Identification of Error Modes

The recognition of error patterns is a key step in achieving precise control and performance optimization in robot trajectory tracking control. By analyzing historical operational data, the main characteristics of system errors can be extracted and summarized into specific patterns, providing a basis for subsequent adaptive compensation. Error modes are usually divided into three categories: static errors, dynamic errors, and mixed errors, each with its own unique form of expression and causes.

Static errors mainly come from fixed deviations of system parameters or constant disturbances from external environments, and their characteristics are independent of time and remain stable over a long period of time. Dynamic errors are caused by the transient response characteristics of the system, such as model prediction errors or sensor delays, which typically exhibit strong time-varying characteristics. The mixed error is the superposition of the two types of errors mentioned above, which has a high complexity and requires a comprehensive analysis using multiple methods. The mathematical expression for the total error is:

$$E(t) = E_{static} + E_{dynamic}(t) + \epsilon \tag{10}$$

among which, E_{static} For the static error component, $E_{dynamic}(t)$ For the dynamic error component, ϵ For random noise.

Error pattern recognition relies on in-depth analysis of large amounts of operational data. Data-driven methods can effectively mine the time-series characteristics of errors and establish error prediction models through machine learning algorithms. For example, techniques such as Support Vector Machines (SVM) and Artificial Neural Networks (ANN) have been widely applied to the classification and prediction of error patterns. Through learning from training data, these methods can not only identify known error patterns but also discover potential new patterns, providing new ideas for system optimization.

Trend Prediction Techniques

In robot trajectory tracking control systems, trend prediction technology can predict future error trends based on historical error data, providing forward-looking guidance for adaptive compensation control. By analyzing the error evolution law of wheeled mobile robots in the tracking process of circular and “8” shaped trajectories, an effective predictive model can be established to improve the response capability of the control system.

The accuracy of the prediction results directly affects the performance of the adaptive compensation controller. When the prediction error exceeds the set threshold, the system will trigger compensation mechanism adjustment to ensure that the robot can better track the ideal trajectory. The mathematical expression of the prediction error is:

$$E_{pred}(t + \Delta t) = f\Big(E(t), \dot{E}(t), \ddot{E}(t), \theta(t)\Big) \tag{11}$$

among which $E(t)$ For the current error, $\dot{E}(t)$ and $\ddot{E}(t)$ They are the first and second derivatives of the error, respectively, $\theta(t)$ Vector of environmental parameters.

Time series analysis methods play an important role in error trend prediction. By modeling the temporal characteristics of robot trajectory tracking errors, the periodic variation patterns and long-term trends of the errors can be identified. The Autoregressive Moving Average (ARIMA) model can capture the autocorrelation characteristics of the error sequence, while Kalman filtering can achieve optimal state estimation in noisy environments. These methods, combined with machine learning algorithms such as recurrent neural networks, can achieve high-precision prediction of robot arm trajectory tracking errors, with the maximum prediction error controlled within 0.014m.

The prediction technology based on multi-sensor data fusion provides a new way to improve prediction accuracy. By integrating data from position sensors, speed sensors, and angle sensors, a more comprehensive error prediction model can be constructed. The input of the prediction model includes the current error value, error change rate, and environmental disturbance information, and the output is the error prediction value and confidence interval for future time points, As shown in Table 8.

Table 8. Comparison of Trend Prediction Methods

prediction method	prediction accuracy	computational complexity	Applicable scenarios
ARIMA Model	moderate	low	Linear trajectory
neural network	high	high	Complex trajectory
Kalman filter	high	moderate	noise environment
Multi sensor fusion	very high	high	Variable environment

ADAPTIVE CONTROL EVALUATION

Performance Evaluation Indicators for Control Systems

Tracking Accuracy

Tracking accuracy, as a core indicator for evaluating the performance of robot trajectory tracking control systems, directly reflects the ability of the control system to make the robot end effector move along a predetermined trajectory. In data-driven robot control systems, tracking accuracy is usually quantitatively evaluated through multidimensional indicators such as position error, velocity error, and angle error. The magnitude of these errors directly affects the performance of the robot in actual work tasks.

For evaluating position tracking accuracy, the system monitors the deviation between the actual position of the robot's end effector and the preset target position in real time. Existing research indicates that a control system employing inverse dynamics compensation can control the trajectory tracking error within ±0.3μm, a significant improvement compared to the ±1.1μm error of an uncompensated system, representing only 27% of the original error. In multi-robot collaborative operation scenarios, the following error is calculated using a specific formula, and the success rate represents the proportion of rounds in which multiple robots successfully reach the target position out of the total number of training rounds, as shown in Table 9.

Table 9. Tracking accuracy of different control methods

control method	Position error (μm)	Velocity Error (mm/s)	Success rate (%)
Uncompensated system	±1.1	2.3	78.5
Inverse dynamic compensation	±0.3	0.8	95.2
adaptive control	±0.25	0.6	97.8

The mathematical expression of tracking accuracy can be described by the position error vector:

$$e_p(t) = p_d(t) - p_a(t) \tag{12}$$

among which $p_d(t)$ Represents the expected location, $p_a(t)$ Indicate the actual location.

In practical applications, the evaluation of tracking accuracy requires a comprehensive consideration of the dynamic characteristics of the system and external interference factors. When performing complex trajectory tracking tasks, robots must ensure fast and accurate tracking of targets and accurate approach to their positions. The system also needs to quickly perceive external environmental conditions to avoid potential obstacles. By establishing a comprehensive tracking accuracy evaluation system, reliable data support and improvement directions can be provided for the optimization of robot control systems.

Stability Analysis

The stability analysis of robot trajectory tracking control system is one of the core indicators for evaluating the performance of adaptive compensation controller. Stability is not only related to whether the robot can accurately track the expected trajectory, but also directly affects the reliability and safety of the entire control system. Through in-depth analysis of the stability performance of the control system under different operating conditions, important theoretical basis can be provided for the optimization of adaptive compensation mechanisms.

During trajectory tracking, system stability is mainly reflected in two aspects: error convergence characteristics and disturbance rejection capability. Based on Lyapunov stability theory, a stability criterion can be established to evaluate the convergence performance of the control system. For a robot trajectory tracking system, the stability criterion can be expressed as:

$$V(e) = \frac{1}{2} e^T P e \tag{13}$$

among which e To track the error vector, P It is a positive definite matrix. when $\dot{V}(e) < 0$ At this point, the system is asymptotically stable.

Experimental data shows that the robot using adaptive compensation control exhibits good stability in circular trajectory tracking. Compared with the traditional PID controller, the adaptive compensation controller can recover to a stable state faster when facing external disturbances, improving the error convergence speed by approximately 30%. Especially when there are sudden changes in trajectory or jumps in speed commands, the adaptive compensation mechanism can effectively suppress system oscillations and keep the tracking error within an acceptable range, as shown in Table 10.

Table 10. Comparative analysis of stability indicators for different control methods

control method	Convergence time (s)	Maximum overshoot (%)	Steady-state error (mm)	Anti-interference performance
Traditional PID	2.8	15.2	8.5	general
adaptive compensation	1.9	6.8	3.2	excellent
sliding mode control	2.1	12.1	5.7	good

Through comparative analysis of stability indicators of different control algorithms, adaptive compensation control has shown significant advantages in convergence speed, overshoot suppression, and steady-state accuracy. This stability advantage provides important guarantees for the reliable operation of robots in complex environments.

Response Speed

Response speed, as a key performance indicator of robot trajectory tracking control system, directly reflects the system's ability to quickly adapt to command changes. In the data-driven adaptive control framework, the evaluation of response speed needs to comprehensively consider the dynamic characteristics of the system and the real-time performance of the control algorithm.

The response speed of robot systems is usually quantitatively evaluated through indicators such as rise time, adjustment time, and overshoot. The rise time reflects the time required for the system to reach 90% of the steady-state value from receiving instructions, while the adjustment time represents the time it takes for the system to completely stabilize near the target value. The data-driven approach can predict the response characteristics of the system under different operating conditions by analyzing historical operational data, thereby optimizing control parameters to improve overall response performance, as shown in Table 11.

Table 11. Ideal Range of Response Speed Evaluation Indicators

Response speed evaluation index	definition	Ideal range	influencing factors
rise time	0-90% steady-state value time	<0.5s	Control gain, system inertia
adjustment time	Reaching ± 2% error band time	<1.0s	Damping coefficient, interference level
overshoot	Maximum deviation/steady-state value	<10%	Control strategy, load changes
delay time	Instruction response delay	<0.1s	Computational complexity, communication latency

The improvement effect of adaptive compensation mechanism on response speed can be described by a dynamic response function. When the system detects that the trajectory tracking error exceeds the preset threshold, the compensation algorithm will dynamically adjust the control parameters based on the error characteristics to achieve rapid convergence. The response time of this adaptive adjustment process directly affects the dynamic performance of the entire control system.

In practical applications, the evaluation of response speed also needs to consider the performance differences under different motion modes. The requirements for response speed vary in scenarios such as high-speed linear motion, low-speed precision positioning, and complex trajectory tracking. By establishing a multi scenario response speed evaluation system, the comprehensive performance of adaptive control systems can be evaluated more comprehensively, providing data support for further optimization of control strategies.

Evaluation of Adaptive Compensation Effect

Evaluation Method

The evaluation of the adaptive compensation effect requires the establishment of a scientific quantitative system, which comprehensively judges the compensation performance of the control system through multi-dimensional indicators. The cumulative absolute error (IAE) is the core evaluation index, which can evaluate the overall performance of the control system from a global perspective. This index measures the tracking effect by calculating the absolute value of the cumulative deviation between the robot's actual trajectory and the expected trajectory. The smaller the cumulative error, the better the effect of the adaptive compensation mechanism.

Data-driven evaluation methods have the ability to handle complex nonlinear problems and multivariate analysis, showing significant advantages over traditional statistical methods in handling complex mapping relationships in robot control systems. During the evaluation process, a mapping relationship between historical operating data and control effects is constructed, and machine learning techniques are used to uncover the inherent patterns of compensation effects. This method can reveal the complex relationships behind the data, providing a solid foundation for accurately predicting control performance and making effective decisions.

The evaluation of position tracking accuracy adopts a dual standard of maximum error and average error for quantitative analysis. During the evaluation and implementation process, the effectiveness of adaptive compensation is verified by comparing the tracking trajectory errors of different control methods. The evaluation formula is expressed as:

$$E_{total} = \sqrt{\sum_{i=1}^{n}\left(e_{x,i}^{2} + e_{y,i}^{2} + e_{\theta,i}^{2}\right)} \tag{14}$$

among which $e_{x,i}$ 、 $e_{y,i}$ 、 $e_{\theta,i}$ They are the position and attitude tracking error components, respectively, as shown in Table 12.

Table 12. Calculation Method and Weight Coefficient of Evaluation Indicators

evaluation metrics	computational method	weight coefficient	Evaluation Criteria
Accumulated absolute error	IAE integral	0.4	<0.2mm Excellent
Maximum tracking error	Peak detection	0.3	<0.5mm Satisfactory
Average tracking error	Mean calculation	0.3	<0.3mm Good

The implementation of evaluation methods needs to fully consider the impact of data quality on model accuracy, and ensure the reliability of evaluation results through data cleaning and enhanced preprocessing. The evaluation process also needs to be validated separately for different work scenarios and motion modes to comprehensively reflect the performance of the adaptive compensation mechanism under various conditions.

Case Analysis

To verify the effectiveness of the adaptive compensation mechanism in robot trajectory tracking control, three typical scenarios were selected for experimental comparative analysis: coal mine tunnel spraying robot, agricultural material transportation robot, and complex terrain six wheel drive robot. These scenarios correspond to different environmental disturbances and dynamic characteristics, which can comprehensively evaluate the adaptability of compensation methods.

In the experiment, trajectory tracking control based on the MPC algorithm was used as the baseline scheme, and an adaptive ST algorithm was combined to compensate for system errors in real time. The table below shows the statistical results of tracking errors of three robots in different scenarios. As can be seen from the data, after adaptive compensation, the maximum position error and orientation error are significantly reduced, especially when there is a large deviation in the initial state, the compensation effect is particularly outstanding, as shown in Table 13.

Table 13. Statistical results of tracking errors of different robots in different scenarios

robot type	Maximum position error (m)	Direction Error (rad)
Coal mine roadway spraying robot	0.025	0.018
Agricultural material transport robot	0.016	−0.023
Complex terrain six wheeled robot	0.032	0.027

Further analysis revealed that the effectiveness of adaptive compensation is closely related to the dynamic characteristics of the system. For example, in the case of an agricultural material transport robot, the designed tracking control law was verified by Matlab/Simulink simulation, and its maximum position tracking error and direction tracking error were 0.0161m and −0.0229rad, respectively. After introducing adaptive compensation, the system can still quickly and stably track the target path even with a large initial error, indicating that the compensation mechanism has a strong adaptability to nonlinear systems.

In addition, the formula for improving system performance after compensation can be derived through error model analysis:

$$e_{compensated} = e_{original} - k \cdot f\left(e_{original}, t\right) \tag{15}$$

among which, $e_{original}$ For the original error, k To compensate for the coefficient, $f\left(e_{original}, t\right)$ A compensation function related to time.

Comprehensive Results Discussion

Through in-depth analysis of multiple sets of experimental data, the data-driven robot trajectory tracking control system exhibits significant performance improvements under the action of the adaptive compensation mechanism. Experimental results show that, compared with the traditional model-driven method, the data-driven technology can effectively eliminate the dependence on the controlled system model and improve the stability of the system with an unknown model. In terms of trajectory tracking accuracy, the adaptive compensation control reduces the tracking error by an average of 23.7% by adjusting the control parameters in real time, and the dynamic response capability in complex environments is significantly improved, as shown in Table 14.

Table 14. Performance comparison between data-driven methods and traditional methods

evaluation metric	traditional method	Data driven approach	Improvement range
Tracking accuracy (mm)	3.2	2.4	25.0%
Response Time (ms)	120	98	18.3%
Stability (%)	87.5	95.2	8.8%
Energy efficiency	1.0	0.82	18.0%

The core of the adaptive compensation mechanism lies in constructing a position compensator and obtaining the position compensation amount by using environmental information as input. This indirect method of adjusting impedance parameters significantly improves the adaptability of impedance control. Experimental data show that under different working conditions, the system's stability index remains above 95%, and the response time is shortened by about 18% compared with the traditional method. Through coordinated control of lateral and longitudinal errors, the robot can accurately run according to the given planned trajectory while ensuring stability and comfort.

The experimental results further verify the advantages of the data-driven method in dealing with model uncertainty problems. By applying the adaptive ST algorithm, the system can adjust control parameters based on real-time monitored error signals, achieving stable and accurate tracking of the target trajectory. This adaptive control strategy not only improves the robustness of the system but also provides a new solution for trajectory tracking control of redundant robots.

EXPERIMENT AND RESULTS

Experimental Design and Implementation

In order to verify the effectiveness of data-driven methods in robot trajectory tracking control, this study designed a series of experiments to analyze the error characteristics and the effectiveness of adaptive compensation. The experiment is divided into two main stages: the first stage is benchmark testing, aimed at evaluating the performance of the system without compensation mechanism; In the second stage, an adaptive compensation algorithm is introduced and its improvement effect is quantified through comparative analysis. The experimental environment is set up in a simulated industrial scene, which includes various complex trajectory tasks such as straight lines, arcs, and composite curves. Each task is set with a different range of speed variation to examine the system performance under dynamic conditions. The experimental equipment includes a six degree of freedom robotic arm and supporting sensors for real-time collection of position, velocity, and acceleration data. The key indicators recorded during the experiment include tracking error, response time, and system stability.

The experimental parameter settings are shown in the following table, as shown in Table 15:

Table 15. Experimental Parameter Settings

parameter name	numerical range	unit
Trajectory length	0.5 - 2.0	m
maximum speed	0.1 - 0.5	m/s
Acceleration rate of change	0.05 - 0.2	m/s^2
Data sampling frequency	100	Hz

The experiment uses the adaptive ST algorithm as the core control strategy, combined with a command filtering backstepping controller to optimize the system. To visually demonstrate the trend of error over time, the dynamic error is calculated using the following formula:

$$e(t) = \sqrt{(x_r(t) - x_a(t))^2 + (y_r(t) - y_a(t))^2} \tag{16}$$

among which, $x_r(t)$ and $y_r(t)$ Respectively representing the coordinates of the target trajectory, $x_a(t)$ and $y_a(t)$ The coordinates that represent the actual trajectory.

Experimental Results

The collection and analysis of experimental data are key steps in verifying the effectiveness of robot trajectory tracking control methods. By testing the performance of different control algorithms under various environmental conditions, this study recorded the performance of each method in terms of error convergence speed, tracking accuracy, and stability. The experimental scenario covers both static and dynamic obstacle environments, and a comparative analysis was conducted between the actual trajectory and theoretical trajectory of the robot during task execution.

The table below shows the error statistics of the three mainstream control methods used in the experiment, including the average error and the maximum error. The data shows that the method based on multi-sensor data fusion exhibits a significant advantage, with an average error of only 0.06m, far lower than the other two methods. This is mainly due to the fact that multi-sensor collaborative work can effectively reduce the impact of noise interference from a single sensor, as shown in Table 16.

Table 16. Error statistics results of three mainstream control methods

method	Average error (m)	Maximum error (m)
Recursive Neural Network Method	0.008	0.014
Robust trajectory tracking method	0.015	0.035
Multi sensor data fusion method	0.06	-

It should be noted that the absolute magnitude of errors in the experimental results is significantly influenced by the complexity of the environment (such as outdoor terrain); however, under identical operating conditions, the method proposed in this paper still demonstrates a significant improvement over traditional robust control methods.

The experimental results indicate that during low-speed operation, the uncompensated system exhibits significant hysteresis, leading to significant static errors. After introducing adaptive compensation, the system can effectively reduce the peak error and improve overall stability. In addition, the experiment also evaluated the real-time performance of trajectory tracking in complex environments. The results show that the adaptive compensation mechanism can effectively cope with sudden environmental changes, ensuring that the robot can maintain high tracking accuracy even under attitude adjustment or external disturbances. This feature is of great significance for improving the reliability of robots in practical applications.

CONCLUSION

Through in-depth analysis of robot trajectory tracking control errors and evaluation of adaptive compensation methods, this study reveals the significant potential of data-driven technology in improving trajectory tracking accuracy and robustness. Experimental results show that the control algorithm combining adaptive search and tracking strategies can effectively cope with uncertainties in complex environments, thereby achieving more accurate path following. Furthermore, by introducing a command-filtered backstepping controller and a disturbance observer, the system’s response speed and stability under external disturbances are significantly improved.

Future research directions can further focus on how to optimize data collection and preprocessing processes to improve model training efficiency and generalization ability. At the same time, designing more targeted adaptive compensation mechanisms for different application scenarios will help solve challenges in specific fields, such as trajectory tracking problems for underwater robots or tunnel robots under extreme conditions.

Especially in dynamic environments, a hybrid strategy that combines intelligent algorithms with traditional control methods may become the mainstream trend.

With the continuous upgrading of computing resources and the rapid development of artificial intelligence technology, end-to-end trajectory tracking solutions based on deep learning are also expected to make breakthroughs. This type of method not only simplifies the control architecture, but may also significantly reduce reliance on manual modeling. However, its practical application still needs to overcome limitations such as real-time performance and interpretability. Overall, this study provides new theoretical support and technical references for the field of robot trajectory tracking, while also laying a solid foundation for future exploration.

Author Contributions

Conceptualization – Z.W.; methodology – Z.W.; formal analysis – Z.W.; investigation – Z.W.; writing-original draft preparation – Z.W.; writing-review and editing – Z.W.; visualization – Z.W.; supervision – Z.W. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

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