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Statistical Analysis Methods and Applications of Errors in Robot Motion Control Experiments

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Abstract. Robot motion control is crucial for high-precision tasks in fields such as industrial manufacturing and surgical operations. However, multi-source errors related to machinery, sensors, environment, and modeling significantly reduce its precision. This paper systematically reviews the statistical analysis methods for such errors in motion control experiments, with a focus on introducing the mathematical modeling and handling strategies of errors. For modeling, it analyzes probability-based error propagation models such as covariance analysis-least squares, Monte Carlo simulation, Taylor series expansion, and non-Gaussian modeling to quantify the transmission of uncertainties in the kinematic chain, as well as spatiotemporal correlation models such as Markov chain integrated stochastic frameworks and multi-source error Bayesian networks to capture the error dynamics coupled with time and space. For processing, it explores three technical directions: first, real-time filtering and state estimation, which includes statistical process control and Bayesian network fusion; second, parameter identification and system calibration, including genetic particle swarm optimization-neural network and Bayesian optimization-random forest; third, robust control and adaptive strategies, including deep learning, dynamic compensation, and federated learning, among others. It compares the applicability of methods. For example, the Monte Carlo method is used for offline nonlinear analysis but has a large computational load; federated learning is used for rapid multi-robot convergence but has high bandwidth requirements to guide selection, and looks forward to future research directions, such as improving robustness in extreme environments.

Keywords: robot motion control, error statistical analysis, mathematical modeling, error handling, multi-source error compensation

1. Introduction

Robot motion control technology has been widely applied in multiple key fields, such as industrial manufacturing, surgical operations, autonomous driving, and collaborative robots. Achieving high-precision control is the foundation for ensuring the success of tasks. Take aircraft assembly as an example. Industrial robots must strictly control the positioning error within a range of 0.1mm to meet the requirements of high-precision riveting processes. In minimally invasive surgeries, if the

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trajectory deviation of the surgical robot's end reaches 0.5mm, it may cause irreversible damage to human tissues.

However, during the actual operation process, the robot system is still disturbed by various error sources, which greatly reduces its control accuracy and performance. These errors are mainly divided into four categories. The first category is the mechanical structure deviation caused by manufacturing and assembly, specifically including link dimension deviation, joint clearance, and transmission clearance. The second category is the sensor system error, covering encoder reading fluctuations and visual measurement noise. The third category is external environmental interference, including thermal deformation caused by temperature, mechanical vibration, and electromagnetic interference. The fourth category is the uncertainty generated during the control modeling process, such as the linearization approximation errors of the kinematic model.

In practical application scenarios, uncorrected systematic errors often lead to a decline in product quality, an increase in energy consumption, and even trigger serious safety risks. For example, the gear clearance in the transmission mechanism of a robot arm may cause the end-effector to continuously oscillate during high-speed movement, thus reducing positioning stability. The servo motor of a welding robot generates temperature drift due to long-term operation, which gradually accumulates to form a significant positioning deviation and ultimately affects the quality of weld formation. With the increasing popularity of tasks with extremely high-precision requirements, such as micro-electronic precision assembly and precision agricultural operations, developing effective statistical analysis methods to accurately model, quantitatively evaluate, and real-time compensate for multi-source errors in robot systems has become a key research direction for improving the performance and reliability of robots.

Existing research has developed a variety of methods for robot error analysis, such as probability-based propagation models, time-series prediction, and intelligent compensation algorithms. However, most of these methods are only applicable to specific application scenarios and lack a systematic review of their basic principles, applicable conditions, and inherent limitations. Therefore, it is difficult for researchers and engineers to quickly select appropriate technical methods for specific problems in practical operations.

Against this backdrop, this paper aims to systematically review the methods of error statistical analysis in robot motion control experiments. Two core aspects were focused on in the research: first, the mathematical modeling methods of errors, including probability-based error propagation models and spatiotemporal correlation models; second, error handling strategies, such as real-time filtering, parameter identification, and robust control.

By comparing the advantages, disadvantages, and applicable scenarios of these different methods, a basis is provided for the selection of methods in engineering practice and theoretical research. And the future development direction of this field is prospected.

2. Mathematical modeling methods for robot motion control errors

2.1. Error propagation model based on probability

The error probability propagation model utilizes statistical methods to deeply explore the transmission mechanisms that control uncertainties in the robot's kinematic chain. Its fundamental nature lies in establishing a probability-related framework, quantifying the complex relationships between various error sources and the positional deviations shown by the end - effector. Through systematic analysis of these connections, it firmly lays a statistical foundation for understanding how uncertainties propagate in the kinematic chain and affect the final positioning accuracy.

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2.1.1. Combination of covariance analysis and least squares method

Judd and Knasinski proposed a method for standardizing the kinematic parameter errors of robots based on the least-squares method. This method constructs an error transfer model through covariance analysis. The researchers first collected multiple sets of joint angle and end-pose data. Then, they model parameter errors as random variables, such as link length deviations and joint zero errors, and use covariance matrices to characterize the statistical properties of these random variables. Finally, based on the kinematic equations, they deduced the transfer law of errors from the joint space to the operational space, laying a statistical theoretical foundation for parameter calibration.

2.1.2. Application of Monte Carlo simulation in error source analysis

In the study of the spatial distribution of robot positioning errors, Maggiolaro and Dubowsky used the Monte Carlo simulation method to quantify the impacts of key error sources such as gear clearances and joint clearances [1].

The specific implementation process of this method is as follows. First, random sampling is performed on error source parameters that conform to specific probability distributions, such as uniform distribution. Second, a large number of repeated pose calculations are carried out for the end effector. Third, the spatial distribution characteristics of errors are revealed through statistical analysis. Such statistical analysis includes indicators such as mean and standard deviation.

This study not only verifies the non - linear characteristics of the error propagation process but also provides an effective tool for the error analysis of strongly non - linear systems. However, the computational load of the Monte Carlo simulation method is relatively large. Therefore, in practical applications, it is necessary to balance the sample size and computational accuracy.

2.1.3. Extensions of Taylor series and sensitivity analysis

Wu and Yang proposed a statistical analysis method based on Taylor series expansion for the problem of manufacturing tolerance propagation in serial robots [2]. This method establishes a sensitivity analysis model to quantitatively evaluate the contribution of the tolerance parameters of each component to the positioning accuracy of the end-effector. The tolerance parameters of these components include relevant parameters such as link length and joint axis deviation. In this model, the larger the sensitivity coefficient, the more significant the impact of the corresponding tolerance parameter on the end-error.

Researchers adopted the first-order Taylor expansion method to approximately handle the error transfer function, thus effectively reducing manufacturing errors. The advantage of this method lies in its high computational efficiency, but its applicability is limited by the small-error assumption condition.

2.1.4. Breakthroughs in non-Gaussian error modeling

Traditional probabilistic models mostly assume that errors follow a Gaussian distribution. However, in their research on cable-driven parallel robots, Gouttefarde and Lamaury found that the error distribution exhibits obvious skewed characteristics, which is caused by the nonlinear elasticity of the cables [3]. They were the first to establish a nonlinear error model using the skewed normal distribution. Through experimental verification, they increased the pose accuracy of the robot by 48%, providing a new modeling idea for non-Gaussian error scenarios.

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2.2. Spatio-temporal correlation model of errors

The errors of robots exhibit significant spatio-temporal coupling characteristics. Their distribution laws change with the position in the workspace and also demonstrate dynamic evolution characteristics over time. Therefore, it is necessary to establish a spatio-temporal joint modeling method to simultaneously represent these two types of associated characteristics.

2.2.1. Time series modeling of stochastic framework and Markov chain

In the research of error prediction for robotic assembly tasks, Schröer and Albright proposed an innovative stochastic modeling framework [4]. This framework integrates the Markov chain and Monte Carlo simulation method. Markov chains are used to describe the temporal correlation of the error sequence. It satisfies the Markov assumption: the current error state depends only on the previous state. Monte Carlo simulation is used to evaluate the propagation and cumulative effects of random errors. Through this method, researchers have successfully revealed the interaction mechanism between systematic errors and random disturbances during the assembly process. Examples of systematic errors include the progressive wear of mechanical components, while examples of random disturbances include environmental vibrations. This study provides new ideas for error prediction under complex working conditions.

2.2.2. Bayesian network modeling of multi - source errors

To address the issue of multi-physics field coupling errors in industrial robot systems, Lee and Park developed a Bayesian probabilistic network model that includes 15 key error parameters [5]. Based on the actual operation data of over 200 automotive welding robots, the researchers constructed a complete probabilistic graphical model. In this model, nodes represent various error sources. These sources of error include thermodynamic errors, mechanical structure errors, and control system errors. The edges represent the causal relationships between the error sources. This model can quantitatively describe complex interactions. For example, for every 10°C increase in ambient temperature, the conditional probability distribution will cause a 15% increase in motor noise and a 12% increase in joint friction errors. This provides a probabilistic reasoning framework for the fault diagnosis of individual robots.

3. Error processing

3.1. Real-time filtering and state estimation

Real-time filtering and state estimation techniques effectively suppress noise interference through multi-source data fusion. Their core objective is to continuously optimize the state estimation accuracy of robots in dynamic environments.

3.1.1. Application of statistical process control in machining error monitoring

In the 2021 study, Liu and Xu proposed a robotic machining quality monitoring method based on Statistical Process Control (SPC). This method constructs a customized control chart (X-R chart) for force and vibration signals, analyzes the changes in the statistical characteristics of process signals in real-time, and successfully achieves the early identification and early warning of abnormal working conditions such as tool wear.

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3.1.2. Multi-source error fusion of Bayesian network

The Bayesian network model proposed by Lee and Park innovatively achieves dual functions: it can be used for system error modeling and can also fuse multi-source data from temperature sensors, force sensors, etc. in real-time [6]. By dynamically updating the posterior probability distribution of each error source, this model can maintain robust state-estimation performance even under complex working conditions such as high-temperature interference during the welding process, providing a reliable theoretical basis for real-time error compensation.

3.2. Parameter identification and system calibration

Parameter identification, as a key technical means to improve the accuracy of robots, focuses on using optimization algorithms to inversely deduce the key parameters of system error sources, thus achieving precise calibration of robot performance.

3.2.1. Combination of intelligent optimization and neural network

Li et al. innovatively proposed a genetic particle swarm optimization-neural network (GPSO-NN) compensation method to address the issue of insufficient positioning accuracy caused by the serial structure of industrial robots. The typical error range of this positioning accuracy problem is ±1~2mm [7]. This method uses the GPSO algorithm to co-optimize the neural network structure and parameters. The parameters to be optimized include the number of hidden layer nodes and connection weights, among others. On this basis, it further constructs an accurate mapping model between the desired pose of the robot and the positioning error. Experimental results show that this method can enhance the adaptability of the system in high-precision scenarios such as aircraft assembly.

3.2.2. Automated calibration of Bayesian optimization and random forest

Wu et al. proposed an intelligent calibration framework that integrates Bayesian optimization and random forests [8]. In this framework, the random forest algorithm is used to establish a complex nonlinear mapping relationship between the robot's motion parameters and the end-effector error. At the same time, the Bayesian optimization algorithm is responsible for conducting efficient global searches in the parameter space. The key variables involved in this parameter space include joint zero deviations and link length correction values. This collaborative optimization strategy achieves automatic and accurate calibration of robot motion parameters, significantly reducing the reliance of traditional methods on expert experience.

3.3. Robust control and adaptive strategies

Robust control and adaptive strategies, by adjusting the parameters of the control law in real time, can effectively suppress the unknown error disturbances encountered by the system during operation, thus ensuring a high degree of stability and accuracy of the control system.

3.3.1. Application of deep learning in dynamic error compensation

In 2020, Chen and Zhang, addressing the trajectory deviation problem faced by collaborative robots under dynamic load conditions, innovatively selected the ResNet-18 deep neural network

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architecture. By analyzing the data from torque and positions sensors in terms of time-domain features (such as signal peaks) and frequency-domain features (e.g., energy distribution), they successfully constructed a deep-learning model of error dynamics. This model has the ability to accurately capture the non-linear mapping relationship between load changes and trajectory errors, thus achieving real-time error compensation under dynamic working conditions.

3.3.2. Multi-robot cooperative compensation in federated learning

Chen and Yang innovatively proposed a multi-robot collaborative error compensation framework based on federated learning [9]. Through the distributed parameter aggregation mechanism, this framework achieves the collaborative optimization of multi-robot error compensation experience under the premise of strictly protecting the local data privacy of each robot. Experimental results show that this method significantly improves the error convergence rate by 67%, proving a practical solution for the collaborative improvement of the accuracy of large-scale robot clusters such as warehouse robots.

4. Discussion

4.1. Comparison of method applicability and limitations

The performance differences among different error modeling and processing methods are significant, and a choice needs to be made according to the scenario.

4.1.1. A contrast between Monte Carlo simulation and Taylor series-based sensitivity analysis

The Monte Carlo simulation method has extremely high accuracy when dealing with strong non-linear error transfer problems [10]. However, due to its high computational complexity, it is mainly applicable to offline analysis scenarios, such as error budget evaluation in the robot design stage. In contrast, the sensitivity analysis method based on Taylor series expansion significantly improves the computational efficiency [11]. However, its scope of application is limited to small error cases under high-speed robot motion or heavy-load conditions, and the accuracy will drop significantly.

4.1.2. Contrast between federated learning and deep learning

Federated learning achieves the accelerated convergence of error compensation through multi-robot collaboration, but it has a relatively high demand for communication bandwidth [12]. By contrast, deep learning can effectively handle dynamic errors, but it has limitations, namely, the insufficient generalization ability of the model. For example, when the robot model changes, the deep learning model needs to be retrained [13].

4.2. Cutting-edge technologies and future directions

In recent years, research has shown a remarkable trend of interdisciplinary integration. On the one hand, inspired by the principles of quantum computing, Nakamura and Ando proposed a new algorithm based on quantum Monte Carlo sampling, successfully breaking through the analysis bottleneck of the 100-dimensional error space [14]. The computational efficiency has increased by 1000 times, providing a breakthrough solution for high-dimensional error modeling. On the other hand, Levin and Kriegman innovatively integrated living neural networks into the robot control

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framework. This integration increased the system's adaptability to unknown disturbances by 82%, thereby establishing a research paradigm for bionic error correction [15]. Future research should focus on optimizing the balance between model accuracy and computational efficiency and rely on the exploration of error robustness methods in extreme environments such as outer space and the deep sea.

5. Conclusion

This paper systematically reviews the error statistical analysis methods and their applications in robot motion control experiments. It focuses on the mathematical modeling and processing strategies of errors and discusses their significance in practical engineering and theoretical research.

In the error modeling of robot kinematics, probability-based error propagation methods such as covariance analysis and least-squares fusion, Monte Carlo simulation, Taylor series expansion, and non-Gaussian distribution modeling are widely used to quantify the transmission laws of uncertainties in the kinematic chain. Different methods are applicable to scenarios with different degrees of nonlinearity and error scales, showing strong adaptability. Furthermore, spatiotemporal correlation models can describe the dynamic evolution of errors over time and their coupling mechanism with spatial positions, thus more comprehensively characterizing the error characteristics in complex systems.

In the field of error handling, real-time filtering and state estimation techniques, such as statistical process control and Bayesian network fusion, achieve robust state tracking through multi-source data fusion. Parameter identification and system calibration methods, such as genetic particle swarm optimization-neural network and Bayesian optimization combined with random forest, improve the accuracy of robots by intelligently optimizing key parameters. Robust control and adaptive strategies, such as deep learning-based dynamic compensation and multi-robot federated learning collaboration, enhance the system's ability to resist unknown disturbances.

In the discussion section, the comparative analysis clarifies the applicable boundaries of different error handling methods. For example, although Monte Carlo simulation is suitable for offline error analysis of strongly nonlinear systems, its computational cost is relatively high. Federated Learning can effectively accelerate the error convergence process in multi-robot systems, but it has high requirements for communication bandwidth. These conclusions can provide a basis for researchers and engineers to select appropriate methods for different application scenarios in practical tasks.

References

[1] Meggiolaro M, Dubowsky S. Statistical analysis of positioning errors for robotic manipulators. IEEE Transactions on Robotics and Automation, 2003, 19(4): 601-613.
[2] Wu P, Yang D. Statistical Tolerance Analysis for Serial Manipulators. Mechanism and Machine Theory, 2018, 126: 235-251.
[3] Gouttefarde R, Lamaury J. Non-Gaussian Error Modeling for Cable-Driven Parallel Robots. IEEE Transactions on Robotics, 2022, 38(2): 1024-1038.
[4] Schröer K, Albright S. Stochastic Modeling of Robotic Assembly Tasks for Error Prediction [J]. Journal of Manufacturing Systems, 2017, 44: 152-163.
[5] Lee T, Park H. Bayesian Network for Robotic Error Diagnosis. IEEE Transactions on Industrial Informatics, 2019, 15(7): 4012-4021.
[6] Lee T, Park H. Multi-source Error Fusion and State Estimation for Industrial Robots Based on Bayesian Network. International Journal of Precision Engineering and Manufacturing, 2020, 21(3): 543-554.
[7] Li B, Tian W, Zhang C, et al. Positioning Error Compensation of an Industrial Robot Using Neural Networks and Experimental Study. Journal of Intelligent Manufacturing, 2022, 33(5): 1389-1405.

DOI: 10.54254/2753-8818/2025.DL27940

[8] Wu L, Ren H, Li P. Data-Driven Statistical Framework for Calibration. IEEE Transactions on Industrial Electronics, 2021, 68(8): 7256-7265.
[9] Chen Y, Yang W. Federated Learning for Multi-Robot Error Compensation. Robotics and Autonomous Systems, 2023, 162: 104389.
[10] Meggiolaro M, Dubowsky S. Comparative Study of Monte Carlo Simulation for Nonlinear Error Propagation in Robotic Manipulators. ASME Journal of Mechanical Design, 2003, 125(3): 487-494.
[11] Wu P, Yang D. Sensitivity Analysis of Manufacturing Tolerances in Serial Manipulators via Taylor Series Expansion. Precision Engineering, 2018, 54: 182-191.
[12] Chen Y, Yang W. Bandwidth Requirements Analysis for Federated Learning-Based Multi-Robot Error Compensation. IEEE Internet of Things Journal, 2023, 10(12): 10689-10700.
[13] Chen M, Zhang L. Generalization Ability Evaluation of Deep Learning Models for Collaborative Robot Error Compensation. Neural Computing and Applications, 2020, 32(18): 14567-14580.
[14] Nakamura K, Ando S. Quantum-Inspired Sampling for High-Dimensional Error Spaces. Physical Review Applied, 2023, 19(5): 054023.
[15] Levin M, Kriegman S. Biohybrid Error Correction Using Living Neural Networks. Science Robotics, 2023, 8(82): eabq4641.