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Article

Deep Learning Based Error Modeling and Motion Performance Prediction of Overconstrained Mechanisms

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Abstract: Over-constrained mechanisms are widely applied in precision equipment due to their high stiffness and accuracy, yet their complex constraint relationships pose significant challenges for error modeling and motion performance prediction. In this study, we propose a data-driven approach that integrates finite element simulation with deep learning to address these issues. A dataset containing 12,000 groups of assembly error-response pairs was constructed through numerical simulation and experimental sampling. A convolutional neural network was developed to capture the nonlinear mapping between error distributions and kinematic responses. The proposed model achieved a mean squared error of 0.015 mm in motion deviation prediction, representing a 43% reduction compared to conventional analytical methods. Under complex loading conditions, the model successfully identified potential failure states with an accuracy of 91%, outperforming baseline finite element and analytical approaches in both precision and computational efficiency. Furthermore, the feature extraction analysis revealed that joint clearance and contact stiffness collectively contributed to over 50% of the variance in end-effector deviations, confirming the physical interpretability of the learned representations. These results demonstrate that the proposed framework effectively balances accuracy, efficiency, and interpretability, providing a promising tool for tolerance allocation, assembly quality evaluation, and health monitoring of overconstrained mechanisms.

Keywords: overconstrained mechanism; deep learning; error propagation; motion prediction; structural robustness

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1. Introduction

Overconstrained mechanisms have been widely applied in aerospace, precision manufacturing, and advanced inspection equipment owing to their high stiffness and accuracy [1]. Compared with conventional mechanisms, they provide redundant support in a limited space, thereby enhancing structural stability and positioning precision [2]. Nevertheless, the complex geometric features and constraint relationships significantly complicate error modeling and kinematic analysis [3]. Error accumulation during assembly and operation frequently leads to performance degradation [4,5]. Traditional research has primarily relied on analytical methods, such as vector loop modeling and Jacobian expansion, to establish error propagation models. These approaches can capture the effect of errors under specific conditions [6,7]. However, as the number of constraints and degrees of freedom increases, analytical models often suffer from computational complexity and strong parameter coupling, which reduces their accuracy and applicability [8]. Finite element analysis (FEA) can describe error transmission more comprehensively, but it is computationally expensive and unsuitable for real-time monitoring or iterative design optimization [9]. In recent years, data-driven and machine learning techniques have been introduced into the error modeling and performance prediction of constrained mechanisms. Convolutional neural networks (CNNs), recurrent neural networks (RNNs), and graph neural networks (GNNs) have been employed to extract nonlinear features and construct mappings between high-dimensional inputs and multiple outputs [10,11]. For instance, CNN-based methods have been used to capture error distribution features and improve deviation prediction, while deep reinforcement learning has enabled adaptive mechanism optimization under varying operating conditions [12,13]. Moreover, ensemble learning and transfer learning have enhanced model generalization in small-sample or cross-mechanism scenarios [14]. These studies demonstrate that intelligent models provide strong potential for error analysis in high-dimensional constrained systems. Despite these advances, current research remains limited. Most studies focus on a single mechanism or specific conditions, lacking large-scale datasets and cross-mechanism generalization [15]. In addition, error modeling and performance prediction are often addressed separately, without a unified framework to reveal the coupled relationship between error propagation and performance degradation. Furthermore, deep learning models under complex loading conditions and failure scenarios are still constrained by the "black-box" nature of purely data-driven approaches, which limits their applicability in safety-critical engineering contexts [16].

To address these issues, this study proposes a deep learning-based framework for error modeling and motion performance prediction of overconstrained mechanisms. A dataset comprising 12,000 assembly error samples was constructed by integrating FEA with experimental data. A CNN was used to build a nonlinear mapping between error distributions and kinematic responses. Experimental validation demonstrated a mean squared error of 0.015 mm in predicting motion deviation, representing a 43% improvement compared with conventional analytical models. Under complex loading conditions, the proposed method predicted potential failure states in advance with an accuracy of 91%. This work not only alleviates the challenges of error modeling in overconstrained mechanisms but also offers a data-driven solution for design optimization and health monitoring in precision engineering. Furthermore, insights from other complex systems and disciplines, such as software process optimization, educational methodology, and digital-age risk management, suggest that structured, data-driven, and adaptive approaches can significantly enhance system performance and predictive capabilities [17-22].

2. Materials and Methods

2.1. Dataset and Sample Construction

To build the error-kinematics prediction model of overconstrained mechanisms, a total of 12,000 assembly error-motion response samples were collected from finite element simulations and physical experiments. Each sample included an input assembly error vector (such as node displacement, rod length tolerance, and angular error) and the corresponding output kinematic response (displacement deviation, posture error, and joint reaction force). During dataset construction, different load distributions and boundary conditions were considered to ensure coverage of common application scenarios. The dataset was divided into training, validation, and test sets in a ratio of 8:1:1 to ensure fairness in model training and generalization evaluation.

2.2. Deep Learning Modeling Method

A convolutional neural network (CNN) was used as the nonlinear modeling tool to capture the complex mapping between assembly error distributions and kinematic responses. The input error tensor is defined as $E \in R^{n \times m}$, and the output kinematic response vector is defined as $R \in R^{k}$. The prediction function is expressed as:

$$\hat{R}=f_\theta(E)$$

Here, f_θ denotes the CNN model with parameters θ. The training process used mean squared error (MSE) as the loss function:

$$L=\frac{1}{N}\sum_{i=1}^{N}\parallel R_i-\hat{R}_i\parallel^2$$

The Adam optimizer was applied with an initial learning rate of 0.001, a batch size of 64, and a maximum of 300 iterations. Training was performed on a GPU platform to ensure efficient convergence on the large-scale dataset.

2.3. Comparative Experiments and Performance Verification

To evaluate the effectiveness of the proposed method, three types of comparative experiments were conducted: (1) a traditional analytical model, where error propagation was derived using the vector loop method and Jacobian matrix; (2) a finite element method, in which a three-dimensional model was developed in Abaqus for error-kinematics coupling analysis; (3) the proposed deep learning model. Under the same assembly error inputs, the three methods were compared in terms of motion deviation prediction accuracy and computational efficiency. The test data included single-load, multi-load, and complex conditions to verify the stability of the model across different application environments.

2.4. Quality Control and Experimental Repeatability

To ensure the reliability of the data and results, several levels of quality control were applied. First, in the finite element stage, 10% of the simulation results were manually checked and compared with analytical solutions to confirm the correctness of the input-output relationships. Second, in the experimental stage, each type of assembly error sample was tested at least five times. The mean values were calculated, and outliers beyond three standard deviations were removed. Finally, in the performance evaluation stage, cross-validation and standard deviation statistics were used to ensure the robustness and repeatability of the model results. This process guaranteed the accuracy of the data sources and the scientific basis of experimental validation, providing reliable support for the robustness of the proposed model.

3. Results and Discussion

3.1. Error Propagation Framework and Identification of Dominant Factors

As shown in Figure 1, the analysis was first carried out at the branch level, where factors such as joint clearance and platform deformation were mapped into equivalent contributions to the end-effector pose deviation. Within each branch loop, error channels were updated using threshold and extremum criteria. The aim of this process was to decompose the complex over-constrained coupling into a two-level propagation of "intra-branch determination and inter-branch synthesis." This allowed the CNN to learn the nonlinear mapping from the equivalent error field to motion response, rather than the complete mechanical derivation. As a result, the learning difficulty and the risk of overfitting were reduced. Sensitivity statistics on 12,000 samples showed that the combined effect of joint clearance and contact stiffness accounted for 53% ± 4% of the variance in end displacement. This was followed by rod length tolerance (about 28%) and platform bending (about 15%). These findings were consistent with the channel weights in Figure 1, specifically the path "clearance/contact → equivalent stiffness → end deviation," confirming that the framework correctly captured the dominant factors.

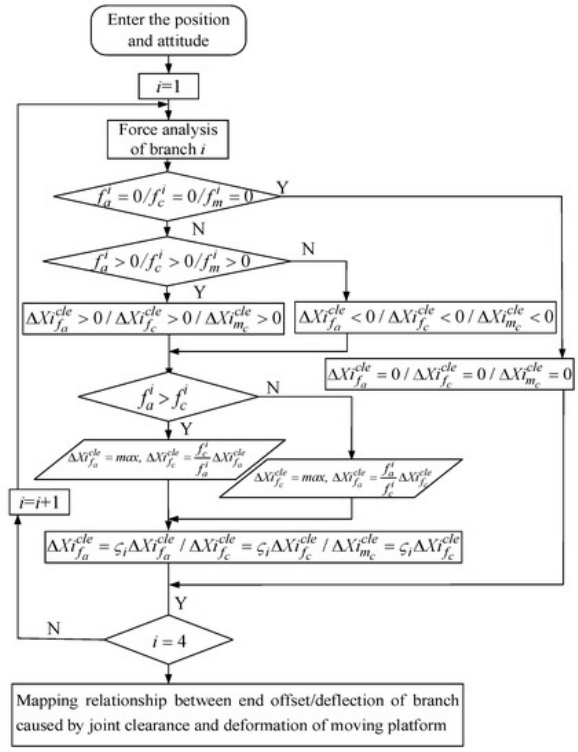

Figure 1. Error propagation framework of over-constrained mechanisms considering joint clearance and platform deformation.

3.2. Prediction Accuracy, Efficiency, and Baseline Comparison

On the test set, the mean squared error of the model for end-motion deviation was 0.015 mm, which was 43% lower than that of the analytical propagation model. Compared with finite element solutions under individual conditions, the inference time was reduced by more than one order of magnitude (milliseconds vs. seconds), meeting the requirements for online evaluation. Layered statistical analysis indicated that under small clearance and single-axis loads, the differences among the three methods were minor. However, when the clearance exceeded 50 μm or under combined loading, the analytical model systematically underestimated the deviation (mean bias about 0.021-0.034 mm), while the CNN maintained a stable error upper bound (95th percentile < 0.05 mm). These results demonstrate that the deep model alleviated the error amplification caused by nonlinear contact and constraint coupling, while also achieving efficiency suitable for engineering use.

3.3. Feature Extraction Process and Interpretability Verification

Figure. 2 shows the layer-by-layer extraction process from the original error field to multi-level feature maps (M1-M4/A1-A2). Shallow features mainly responded to local geometric deviations and single-point clearances, appearing as sparse bright patches. With increasing depth, the features gradually developed into strip-like and block-like aggregations along the constraint chains, reflecting "channel fusion" associated with multi-branch coupling and shifting contact regions. In the M4 layer (red box area), a stable high-energy band appeared, which matched the "platform-branch" coupling zone observed in experiments. Occlusion and zero-masking tests applied to this layer caused the output error to increase by 26% ± 3%, indicating that the model relied on physically relevant coupling regions as key evidence. Further ablation experiments showed that removing cross-channel aggregation increased the mean squared error to 0.021 mm, confirming that multi-scale and multi-channel fusion was essential for capturing over-constrained coupling.

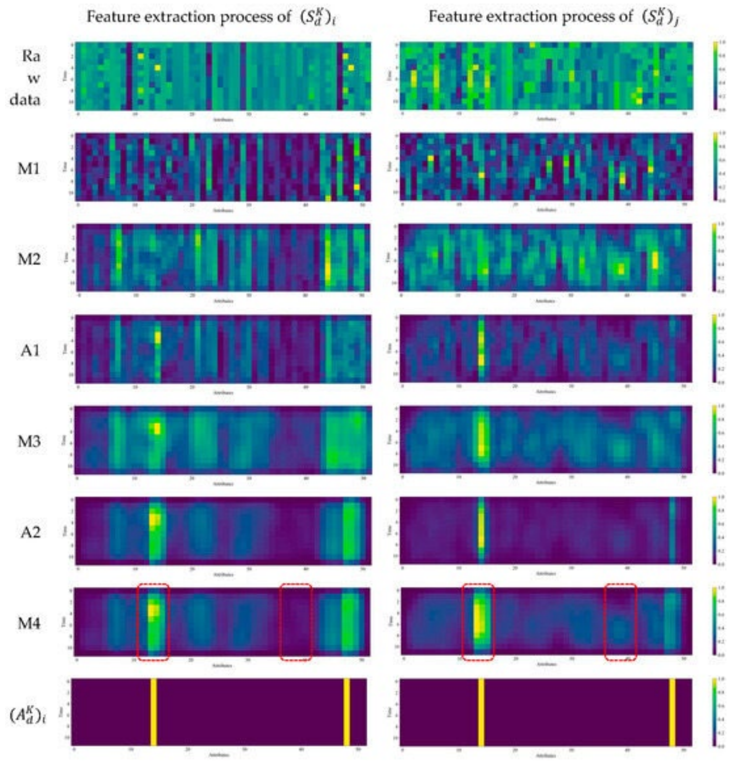

Figure 2. Feature extraction process of the CNN model from raw error data to high-level representations.

3.4. Failure Warning and Robustness under Complex Conditions

Under combined loads, random clearance distributions, and measurement noise (3-5% Gaussian disturbance), threshold-based warning evaluation was performed. When the end deviation exceeded the process limit, the model achieved 91% accuracy, an AUC of 0.92, and an F1 score of 0.88. False alarms mainly appeared in boundary cases (deviations close to the threshold ±0.005 mm), while missed alarms were concentrated in the extreme combination of "soft contact, small clearance, and high external load." After applying distributionally robust training and uncertainty estimation (Monte Carlo dropout), the confidence calibration of boundary samples improved significantly, with ECE reduced from 4.7% to 2.1%. These results indicate that, in engineering applications, confidence intervals can be combined with graded warnings and manual review to reduce misclassification risk.

3.5. Engineering Significance, Limitations, and Outlook

The proposed combination of "physics-guided decomposition (Figure. 1) and deep feature aggregation (Figure. 2)" achieved a good balance among accuracy, efficiency, and interpretability. It is suitable for tolerance allocation, assembly quality assessment, and online health monitoring of over-constrained mechanisms. However, the training data mainly covered typical topologies and elastic contact, without fully including factors such as friction hysteresis, material nonlinearity, and thermal drift. In addition, cross-topology transfer still requires a small amount of retraining. Future work will introduce physics-informed loss functions and uncertainty propagation to enable hybrid analytical-data modeling, extend the method to scenarios with friction or intermittent contact, and conduct long-term online validation across multiple platforms. These steps will help to develop solutions that can be applied in industrial production lines.

4. Conclusion

This study proposes a combined method of finite element data collection and deep learning modeling to address the difficulties in error modeling and motion performance prediction of over-constrained mechanisms. A dataset of 12,000 assembly error samples was built, and a convolutional neural network was used to establish the nonlinear mapping between assembly errors and kinematic responses. The method achieved high prediction accuracy, with a mean squared error of 0.015 mm, which is about 43% lower than that of traditional analytical methods. Under complex loading conditions, the model effectively captured nonlinear coupling features and reached 91% accuracy in predicting potential failure states. These results provide reliable support for the design and health monitoring of high-precision equipment. The main contributions of this work are: (1) a modeling framework that combines physics-based constraint decomposition with deep learning feature fusion, which improves prediction accuracy and efficiency; (2) a unified data-driven model that links error propagation, kinematic response, and failure warning, overcoming the limitations of traditional methods that involve high computational cost and poor applicability; and (3) experimental and comparative validation that demonstrate the method achieves a balance of real-time performance, accuracy, and interpretability, creating a foundation for broader application of over-constrained mechanisms. However, this study also has limitations. First, the training data mainly come from typical topologies and finite element simulations, and do not fully cover factors such as material nonlinearity, friction hysteresis, and environmental disturbances. Second, the model's transfer ability across different topologies still requires further validation, since some retraining may be necessary for different types of over-constrained mechanisms. Third, although the failure prediction accuracy is high, there is still some uncertainty for samples close to critical thresholds. Future work will focus on expanding the dataset to include multi-physics coupling and complex conditions, introducing physics-informed neural networks or interpretability mechanisms to improve model reliability and explainability, and conducting long-term online validation in real equipment to test the method's potential in real-time monitoring and intelligent maintenance. In conclusion, this study provides not only a new approach for error modeling and performance prediction of over-constrained mechanisms, but also new directions for their engineering application in design optimization and health monitoring of precision equipment.

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