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DESIGN OF HIGH PRECISION CONTROL ALGORITHM FOR MULTI-AXIS MECHANICAL LINKAGE BASED ON TRANSFORMER MODEL

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Abstract - Multi-axis linkage high-precision control technology is one of the core technologies in high-end equipment manufacturing, CNC machining and industrial robots. Traditional model-based control methods often have limitations in control accuracy and robustness due to their strong dependence on precise mathematical models when dealing with complex nonlinear, strong coupling and time-varying working conditions. To address this problem, this study proposes a paradigm shift from conventional calculus-based control to attention-based control, framing the multi-axis linkage control problem as a time series translation task. Based on the historical data of multi-axis operation, this framework constructs a sequence-to-sequence mapping model using the Transformer architecture. With the self-attention mechanism, this method extracts and models global features from multi-axis continuous historical state sequences, effectively capturing the dynamic coupling relationships between axes. Simulation results demonstrate that compared with traditional PID control and cross-coupling control strategies, the proposed control algorithm shows significant advantages in trajectory tracking accuracy, multi-axis synchronization performance, and disturbance rejection capability, validating the effectiveness of this data-driven translation paradigm for complex linkage control scenarios.

Keywords: Transformer model, Multi-axis linkage system, High precision control, control algorithm.

1. Introduction

Multi-axis mechanical linkage systems are core components of modern high-end manufacturing equipment and automatic production lines, widely applied in CNC machine tools, industrial robots, semiconductor manufacturing equipment, precision assembly systems, and beyond. With the continuous advancement of intelligent manufacturing, these mechanical systems are evolving toward high speed, high precision, and high synergy, imposing increasingly stringent requirements on multi-axis motion control performance. In practical system operation, each axis must achieve high-precision trajectory tracking while maintaining excellent synchronization and coordination under conditions of strong coupling, strong nonlinearity, and time-varying uncertainty between axes. However, numerous factors—such as flexible characteristics of mechanical structures, backlash effects in transmission links, friction-induced nonlinearities, and various external disturbances—complicate the multi-axis linkage control problem, making accurate modeling difficult and introducing significant parameter uncertainty.

Multi-axis linkage and high-precision control are the core research topics in modern precision manufacturing and high-grade equipment systems. Ma and his team designed and built an on-line laser texturing system with seven-axis synchronous linkage to meet the requirements of free-form surface machining. With the integrated design and synchronous control strategy at the system level, they actually verified the feasibility of multi-axis high-precision cooperative motion in complex machining scenes, which provided important reference value for multi-axis linkage system to carry out engineering practice [1]. On the control algorithm level, Zhou et al. proposed a relatively coupled explicit model predictive control method, and combined it with Kalman filter technology to realize sensorless operation mode, which significantly improved the precision of multi-axis contour control, and reflected the application advantages of advanced control algorithms in complex multi-axis systems [2].

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In addition to the electromechanical system itself, high-precision positioning and measurement is an indispensable and important supporting link to realize linkage control. Qi et al. proposed a high-precision positioning method for shield with the help of dual-axis hybrid inertial navigation system. By fusing multi-source information, the positioning accuracy was greatly improved, and the research also showed the potential of data fusion idea in improving the accuracy of complex systems [3]. Li et al. established a fairly accurate dynamic model for the fast rotating mirror system in space laser communication, and introduced sliding mode control strategy to realize high-precision control under high dynamic conditions, which provided a very valuable reference for the control problem of the system with strong nonlinear characteristics [4]. In the compensation and perception of precision system, Su et al. successfully completed the friction compensation of telescope system by identifying LuGre friction parameters with high precision, which significantly improved the tracking performance of the system [5]; However, Li et al. successfully achieved high-precision measurement of the underground explosion source point with the help of the fusion of multi-dimensional vibration sensing information, and verified the effectiveness of the multi-source data-driven method in complex actual working conditions [6]. At present, considerable progress has been made in the design of multi-axis system architecture, the development of new control algorithms and the realization of high-precision sensing ability. However, how to treat and solve the time sequence characteristics of multi-axis system, deal with the coupling relationship between components in the system and carry out unified modeling is a research direction that needs to be explored more deeply.

Traditionally, multi-axis control has relied on calculus-based methods, where differential equations describe system dynamics and controllers are designed based on physical models. While PID control and cross-coupling control have achieved considerable success in industrial applications, their performance fundamentally depends on the accuracy of the underlying mathematical models. When facing complex nonlinear dynamics and time-varying working conditions, these methods often exhibit limitations in control accuracy and robustness because they cannot fully capture the intricate temporal dependencies and coupling relationships inherent in multi-axis systems. Literature review indicates that considerable progress has been made in multi-axis system architecture design, novel control algorithm development, and high-precision sensing capability realization. However, how to treat and solve the time sequence characteristics of multi-axis systems, deal with the coupling relationships between components, and conduct unified modeling remains a research direction requiring deeper exploration.

To overcome these limitations, this study proposes a paradigm shift from conventional calculus-based control to attention-based control, framing the multi-axis linkage control problem as a time series translation task. Rather than relying on explicit physical modeling, this approach leverages the Transformer's self-attention mechanism to learn the dynamic evolution laws directly from historical operational data. By treating the sequence of past multi-axis states as a source "sentence" to be translated into future control instructions, the model can capture both temporal dependencies and cross-axis coupling relationships in a unified manner. This sequence-to-sequence translation paradigm offers a fundamentally new perspective on multi-axis control, moving beyond local error correction toward global sequence modeling. The following sections detail the methodology, experimental validation, and comparative analysis of this approach against traditional control methods.

Under the complex and nonlinear working conditions, the multi-axis mechanical linkage control technology still faces several key problems, such as the control accuracy is not ideal, the synchronization error accumulates with the running time, and the robustness of the whole system is limited [7]. Therefore, it is necessary to develop a control method, which can describe the dynamic characteristics of the time series of the system at the same time and effectively characterize the coupling relationship between multiple axes. Based on this background, the focus of this study is on multi-axis mechanical linkage system, and the goal is to design a high-precision control algorithm based on Transformer architecture. With the help of self-attention mechanism, the algorithm will model the state of multi-axis system and their historical trajectory information in a unified way, and realize the global perception and more accurate prediction of the dynamic behavior of the system. In terms of research methods, the technical route of combining data-driven modeling with deep learning control is mainly adopted to construct a Transformer network structure oriented to control tasks, and its output is mapped into instructions for multi-axis collaborative control, which improves the trajectory tracking accuracy and synchronous control performance of the system [8]. This study is not only to explore a new technical path for the application of Transformer model in the field of mechanical control, but also to provide theoretical and engineering reference for breaking through the performance bottleneck of traditional multi-axis control methods under complex working conditions. This has certain reference value and engineering significance for promoting the practical application of intelligent control algorithm in the field of high-end equipment manufacturing.

2. Materials and Methods

2.1 Multi-Axis System Data Acquisition And Data Set Construction

2.1.1 Dynamic Description of Multi-axis Mechanical Linkage System

Multi-axis mechanical linkage system is usually composed of multiple actuators, transmission structures and control units, and its dynamic behavior is multi-input multi-output (MIMO) system, and there is a significant coupling relationship among the motion axes. Let the system contain n motion axes, and the expression of its generalized coordinate vector is shown in Formula (1):

$$\mathbf{q}(t)=[q_1(t),q_2(t),\ldots,q_n(t)]^T \tag{1}$$

Wherein $q_i(t)$ it represents the displacement state of the i-th axis at time t. Considering the inertia, damping, stiffness and nonlinear friction of the system, the unified expression of the dynamic equation of the multi-axis mechanical linkage system is shown in Formula (2):

$$\mathbf{M}(\mathbf{q})\ddot{\mathbf{q}}+\mathbf{C}(\mathbf{q},\dot{\mathbf{q}})\dot{\mathbf{q}}+\mathbf{G}(\mathbf{q})+\mathbf{F}(\dot{\mathbf{q}})=\boldsymbol{\tau} \tag{2}$$

Among them, the $\mathbf{M}(\mathbf{q})$ inertia matrix represents Coriolis force and $\mathbf{C}(\mathbf{q},\dot{\mathbf{q}})$ centrifugal force, the $\mathbf{G}(\mathbf{q})$ gravity or equivalent load term describes friction and $\mathbf{F}(\dot{\mathbf{q}})$ unmodeled dynamics, and it is the $\boldsymbol{\tau}$ control input vector.

The "fixed time step" refers to the consistent interval at which the multi-axis system's state is sampled for control purposes. In this study, the sampling rate is set to 1 millisecond, ensuring that the data collection is synchronized with the controller's clock cycle. This synchronization is crucial for accurate trajectory tracking and system coordination in multi-axis CNC systems, as the control algorithm must operate within the time constraints of the system's real-time processing capabilities. By aligning the sampling rate with the controller's clock, this study ensures that the control commands are generated in a timely manner, maintaining high precision and synchronization across all axes. This synchronization also validates the precision claims of the control algorithm, as the performance is evaluated based on the consistency of the sampling rate with the control system's clock cycle, ensuring that the trajectory tracking and synchronization accuracy meet the system's operational requirements.

In practical engineering application, the system parameters are often difficult to be accurately obtained, and will change with the change of working conditions. The dynamic model can only be used as an approximate description, and it is difficult to fully and accurately reflect the actual behavior of the real system. The uncertainty of this model and the nonlinear characteristics of the system make the control method based on accurate model have some limitations, and also provide realistic basis for introducing data-driven modeling and control methods [9]. This research does not depend on the accurate modeling of system dynamics, but on the data sequence to learn the relationship between the input and output of the system, so as to realize the implicit modeling of complex multi-axis linkage dynamic behavior.

2.1.2 Formalization of High Precision Control Problem

In order to realize the high-precision control of multi-axis mechanical linkage system, it is necessary to make a clear mathematical formal description of the control objectives. Let the expected trajectory of the system be as shown in Formula (3):

$$\mathbf{q}*d(t)=[q*d1(t),q_{d2}(t),\ldots,q_{dn}(t)]^T \tag{3}$$

If the corresponding actual output trajectory is $\mathbf{q}(t)$, the trajectory tracking error is defined as shown in Formula (4):

$$\mathbf{e}(t)=\mathbf{q}_d(t)-\mathbf{q}(t) \tag{4}$$

The core of high-precision control is to realize the continuous reduction of tracking error during the whole system operation, and to ensure the synchronization and coordination ability between multi-axis movements to be maintained. Generally, synchronization error is defined as a function of relative motion deviation between axes, such as the error difference between adjacent axes or master-slave axes [10]. The control problem can be summarized as follows: under the condition that the system stability and input constraints are satisfied, the control law $\boldsymbol{\tau}(t)$ is designed so that the $\mathbf{e}(t)$ synchronization error can converge to the allowable range set in advance in a limited time.

The Transformer model used in this study directly learns the "invisible" defects of the system, such as vibrations or friction, from historical data rather than relying on perfect mathematical models. This ability to capture unmodeled dynamics through data-driven methods distinguishes it from traditional PID control, which requires accurate physical modeling to compensate for disturbances.

In the data-driven control framework, the above problems can be transformed into a sequence-to-sequence mapping, which can predict the optimal control instructions needed at the current or next moment by virtue of the multi-axis state sequence and historical control input of the system in the past time period. The formal representation is shown in Formula (5):

$$\boldsymbol{\tau}(t) = f_{\theta}\left(\mathbf{x}(t-T:t)\right) \tag{5}$$

Among them, the $\mathbf{x}(t-T:t)$ multi-axis state sequence in the time window is $f_{\theta}(\cdot)$ a nonlinear mapping function determined θ by the parameters of Transformer model. Through this formal description, the high-precision multi-axis linkage control problem is naturally transformed into a learning problem based on time series modeling, which lays a theoretical foundation for the structural design and training strategy of the subsequent Transformer control algorithm.

By leveraging the self-attention mechanism, the model learns the underlying system behaviors and dynamics from the historical state sequences, allowing it to adapt to various nonlinearities and uncertainties, such as friction and vibration, without explicitly modeling them. This approach enhances the robustness of the control system, enabling it to perform effectively under diverse operating conditions, even when detailed system dynamics are difficult to describe mathematically. The model’s capability to learn from the data allows for better handling of nonlinear effects, improving trajectory tracking accuracy and synchronization, especially in the presence of disturbances that traditional methods might struggle to compensate for.

2.2 Core Algorithm Design

2.2.1 Overview of the Overall Architecture

Aiming at the specific challenges of multi-axis mechanical linkage system—strong correlation in time series, complex coupling relationships between different motion axes, and high demand for control accuracy—this study designs and builds a general framework for multi-axis high-precision control based on the Transformer model. The core innovation lies in reconceptualizing the control problem as a sequence-to-sequence translation task: the historical operational data of the multi-axis system within a continuous time window serves as the source sequence, which is encoded and then decoded into future control instructions as the target sequence. Through the self-attention mechanism, this framework achieves global modeling of state characteristics across different time steps and different motion axes, generating control instructions that meet the requirements of high-precision trajectory tracking and synchronous control. The workflow of the entire algorithm is as follows: serializing and encoding the running state of the multi-axis system from the past time window; using the Transformer encoder to extract features from the multi-dimensional time series, capturing the dynamic evolution laws of the system; leveraging the decoding module to map high-dimensional features into control input signals corresponding to each axis. This architecture substantially reduces dependence on accurate physical models while fully utilizing historical data under complex working conditions to improve the overall performance of multi-axis collaborative control.

The Transformer model in this study is trained based on historical data that represents the system's behavior under specific conditions. If the mass of the robotic arm changes by 10%, the model's performance may be affected because it was trained on data corresponding to the original mass parameters. While the model is capable of adapting to small variations in the system, a significant change in the system's mass could introduce new dynamics that were not accounted for in the original training data. As such, retraining the model with new data reflecting the updated system parameters would likely be necessary to maintain optimal performance. The data-driven nature of the Transformer model allows it to learn the system's behavior, but its ability to adapt to significant changes in system dynamics is limited by the representativeness of the training dataset. Therefore, while the model can generalize to some extent, a large shift in system characteristics, such as mass, would require retraining to ensure accuracy in control.

In this study, the Transformer model is designed to handle typical variations in system conditions, such as slight changes in load or tool usage, without requiring retraining. However, if the system experiences substantial changes, such as a significantly heavier load or the use of a different tool, the model's performance may degrade due to differences in the underlying dynamics that were not represented in the training data. Since the model is data-driven, it learns the system behavior based on the data it was trained on. Significant changes in the system, such as alterations in the load or tool characteristics, could introduce new dynamics that the model has not encountered. In such cases, retraining the model with updated data reflecting these changes would be necessary to maintain high precision and synchronization. Therefore, while the model is flexible enough to adapt to minor variations, large shifts in the system's operating conditions will require retraining to ensure that the model continues to perform optimally.

2.2.2 Overview of the Overall Architecture

Aiming at the specific challenges of multi-axis mechanical linkage system, such as strong correlation in time series, complex coupling relationship between different motion axes and high demand for control accuracy, this study designs and builds a set of general framework of multi-axis high-precision control algorithm based on Transformer model, which takes the operation data of multi-axis system in continuous time window as the main input, and globally models the state characteristics of different time points and different motion axes through self-attention mechanism to generate control instructions that can meet the requirements of high-precision trajectory tracking and synchronous control [11].

The flow of the whole algorithm is as follows: Serializing and coding the running state of multi-axis system in the past; Using Transformer encoder to extract the characteristics of multi-dimensional time series and grasp the law of dynamic change of the system; With the help of decoding module, high-dimensional features are mapped into control input signals corresponding to each axis. The architecture greatly reduces the dependence on accurate physical model, and can make full use of historical data under complex working conditions to improve the overall performance of multi-axis collaborative control.

2.2.3 Input Sequence Coding

In this study, the multi-axis state sequence of fixed-length time window is regarded as the input of Transformer model. Each time step contains multiple physical quantities, which can comprehensively describe the running state of the whole system. For example, the position, speed and historical control quantity are selected as the main input characteristics of the shaft-machine linkage system, and the data are normalized before being input into the model.

Let the length of the time window be T , and the expression of the input sequence is shown in Formula (6):

$$\mathbf{X} = [\mathbf{x}_{t-T+1}, \mathbf{x}_{t-T+2}, \dots, \mathbf{x}_t] \tag{6}$$

In order to enhance the expression ability of time sequence information, position coding is superimposed on the input features, so that the model can distinguish the data features of different time steps.

2.2.4 Attention Mechanism Design

Transformer model uses self-attention mechanism to model the key time steps and related features of the input sequence. In the multi-axis mechanical linkage control, this mechanism can adaptively pay attention to the historical state which has great influence on the control performance according to the current control goal [12]. With the help of this process, the modeling ability of the model for long-term dependence and coupling relationship between axes will be improved.

Its core calculation form is shown in Formula (7):

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d}}\right)V \tag{7}$$

Through the multi-head attention structure, the model can learn the dynamic characteristics of the system from different feature subspaces at the same time, so that it can maintain stable control performance in high-speed motion or disturbance environment.

The Transformer model in this study utilizes the self-attention mechanism to capture global features from the entire multi-axis system's historical states. Unlike traditional models that focus only on the dynamics of individual axes, the self-attention mechanism enables the model to simultaneously attend to the historical interactions between all axes. This allows for a more comprehensive understanding of how the movement of each axis influences others, enabling the prediction of the next best control command based on the global system state. By processing the time-series data from the system's operation, the model effectively captures the dynamic coupling between axes and uses this global perspective to generate more accurate and synchronized control instructions. This approach significantly improves the trajectory tracking accuracy and synchronization performance, as it accounts for the interdependencies across all axes rather than treating each axis in isolation.

2.2.5 Decoding and Control Output

The high-dimensional feature vectors output by the Transformer model encoder are mapped into control instructions that can directly drive the actuators through the feedforward decoding network. In this study, the vector is mapped to the driving force or torque control required by each axis. In order to improve the synchronization control accuracy of multi-axis system, an additional synchronization error compensation item is added in the output layer to carry out online correction of the relative deviation between the axes.

The expression of the control output is shown in Formula (8):

$$\boldsymbol{\tau}(t) = g(\mathbf{H}_t) \tag{8}$$

Where $\mathbf{H}_t$ is the output characteristic of Transformer at time *t*.

Table 1. Output data samples of 1Transformer control algorithm

Time step	Axis1Control output(nm)	Axis2control output(nm)	Axis3control output(nm)	Maximum synchronization error(mm)
t	1.47	1.45	1.46	0.021
t+1	1.49	1.48	1.48	0.018
t+2	1.52	1.50	1.51	0.015
t+3	1.54	1.53	1.53	0.013
t+4	1.56	1.55	1.55	0.011

As shown in Table 1, with the effect of Transformer control strategy, the output of multi-axis control tends to be consistent, and the synchronization error gradually decreases, which shows that the algorithm can effectively improve the synchronization control performance of multi-axis linkage system while ensuring the trajectory tracking accuracy.

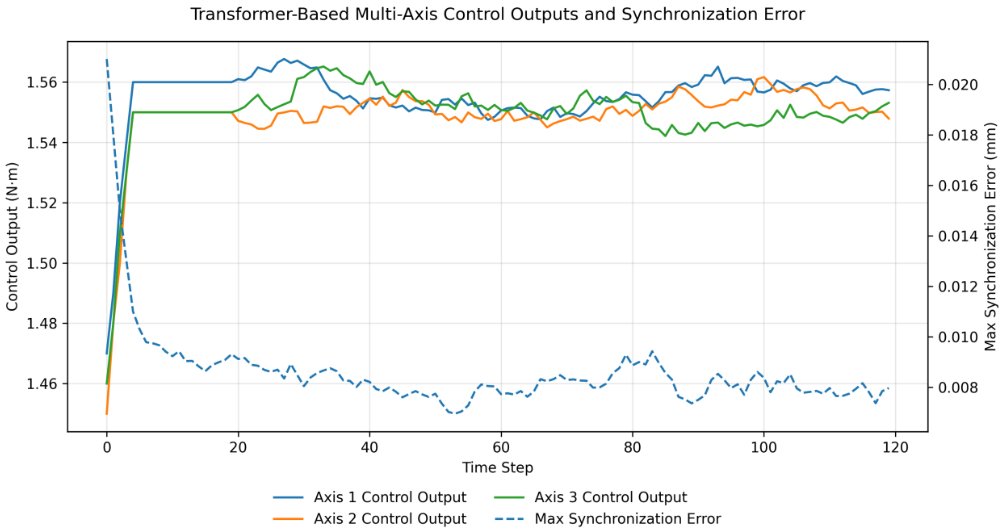

Figure 1: Evolution curve of decoder control output and multi-axis synchronization error of 1Transformer

As shown in Figure 1, Figure 1 is a multi-axis control output curve based on Transformer model and the situation in which the maximum synchronization error changes with time. When the system is running, in order to meet the set trajectory tracking requirements, the control output of each motion axis must be adjusted quickly; At this stage, because the system has not completely entered the stable state, the synchronization error between the axes seems to be large. As the effect of Transformer decoding control strategy is gradually exerted, the control outputs of the three axes begin to become consistent, and finally stabilize at the control level close to each other, which shows that the decoding network does have the ability to generate coordinated control instructions. When entering a steady state, the control output of each axis only shows a small fluctuation, which is consistent with the closed-loop control characteristics of the mechanical system under the influence of various factors such as friction, external interference and parameter uncertainty. The maximum synchronization error curve shows an obvious downward trend, and finally it can converge to a relatively small numerical range, so the compensation mechanism for synchronization error in decoding can really restrain the relative deviation between the axes.

2.3 Training Strategy and Implementation

2.3.1 Data Set Generation

In order to make the multi-axis high-precision control algorithm based on Transformer have better generalization performance and stronger robustness, the training data set is constructed by combining simulation data with actual system operation data. Most of the data come from the running process of multi-axis mechanical linkage system under various trajectory types, different running speeds and changes in load conditions [13]. By adjusting the reference trajectory parameters and control conditions, sample data covering various dynamic characteristics can be generated, thus improving the adaptability of the model in complex scenes.

In the process of data generation, a fixed time step is used to sample the system state. Each sample contains a multi-axis state sequence in several consecutive time steps and its corresponding optimal control output. In order to avoid the situation that the data set may be too single, when constructing the data set, both the steady-state motion stage data and the dynamic change stage data are consciously included. The model can not only learn the characteristics of the stable operation of the system, but also effectively deal with the non-stationary processes such as acceleration and deceleration. The whole data set is divided into three parts: training set, verification set and test set, which are used to train the model, optimize the parameters and evaluate the performance of the model respectively [14].

To address the concern regarding the "overly homogeneous" dataset, this study emphasizes the importance of "data diversity" in the construction of the training dataset. A specific balance between steady-state data and dynamic changes (acceleration/deceleration) is crucial. In this study, the dataset is designed to ensure that it includes a sufficient amount of dynamic data to prevent overfitting, particularly during periods of rapid motion changes. The ratio of steady-state to dynamic data is approximately 60%-40%, ensuring that the model is exposed to a diverse set of conditions. This helps the Transformer model avoid overfitting to steady-state conditions, which could lead to performance degradation during fast motion phases. By including dynamic data in adequate proportions, the model learns to generalize better, improving its robustness under varying operational conditions. This ensures that the model performs reliably, even during fast changes in motion, thus enhancing its ability to handle real-world scenarios where such conditions frequently occur.

The "optimal control output" for each sample is derived from an expert PID controller, which is designed to generate the best control actions based on the system's dynamic states. This output serves as the ground truth for the training dataset, enabling the Transformer model to learn the mapping between system states and the corresponding control actions. The quality of the model's predictions depends directly on the quality of the data generated by the PID controller. As the model is trained on these optimal control outputs, it can only achieve performance within the limits of the PID controller’s design. Therefore, while the model is able to generalize well to real-world conditions, its optimality is constrained by the accuracy and limitations of the reference provided by the expert PID controller.

2.3.2 Loss Function Design

In order to achieve the high-precision control goal of multi-axis mechanical linkage system, the design of loss function should take into account the precision requirements of trajectory tracking and the synchronization performance between multiple axes. In this study, the position tracking error term and the inter-axis synchronization error term are comprehensively introduced in the training process, so that the model can effectively suppress the deviation between different shafting while reducing the single-axis error, thus achieving a coordinated and high-quality motion control effect.

The loss function in this study is designed to balance trajectory accuracy and synchronization performance by combining the trajectory tracking error and synchronization error terms. Specifically, the loss function consists of two main components: the position tracking error for each axis and the synchronization error, which measures the relative motion deviation between axes. The total loss is a weighted sum of these two components, allowing for a flexible trade-off. The weights assigned to each term determine the relative importance of trajectory accuracy versus synchronization performance. In this case, trajectory accuracy is prioritized with a higher weight, while synchronization performance is balanced to ensure that all axes maintain proper coordination. The loss function thus enables the model to minimize both errors simultaneously while maintaining a balance between achieving accurate trajectory tracking and reducing synchronization errors. This approach ensures that the system performs optimally under a range of operational conditions, adapting to the dynamics of the multi-axis system without compromising on either aspect.

In the concrete implementation, firstly, the trajectory tracking error generated by each motion axis is calculated; The maximum synchronization error of the statistical system in the current time step; The weighted fusion of the above two error indexes is used as the optimization goal of the model in the training stage. This design is helpful for the guidance model to give consideration to both trajectory tracking accuracy and multi-axis collaborative performance when generating control output, and can effectively avoid the problem that the overall coordination of the system may decrease due to the optimization of single-axis performance.

Table 2. Changes of loss value under different training rounds

Training rounds	Average trajectory error (mm)	Maximum synchronization error (mm)	Comprehensive loss value
10	0.082	0.036	0.118
30	0.056	0.025	0.081
50	0.039	0.018	0.057
80	0.027	0.013	0.040
120	0.019	0.009	0.028

As shown in Table 2, with the increase of training rounds, the trajectory error and synchronization error all show a continuous downward trend, which shows that the designed loss function can effectively guide the model to gradually converge and improve the overall control performance of the multi-axis system.

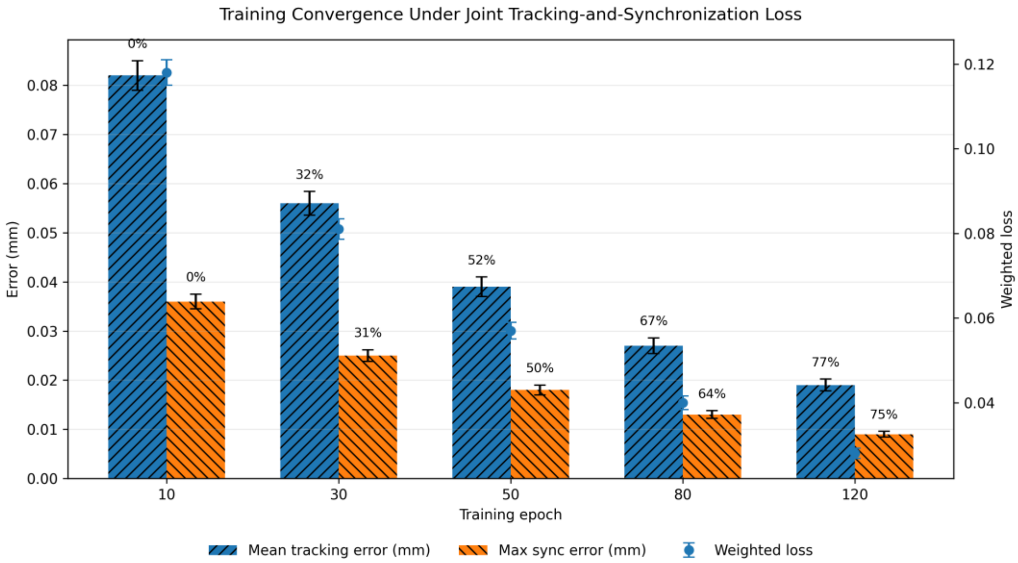

Figure 2: Comparison diagram of training convergence characteristics under joint tracking-synchronization loss constraint

As shown in Figure 2, the grouping histogram gives the average trajectory error and the maximum synchronization error under different training rounds, and reflects the fluctuation of training batches in the form of error lines; The scattered points on the right axis represent the comprehensive loss value, which is used to describe the downward trend of the overall optimization goal. It can be observed that with the increase of training rounds from 10 to 120, the average trajectory error decreased from 0.082mm to 0.019mm, and the maximum synchronization error decreased from 0.036mm to 0.009mm, both of which showed continuous convergence, indicating that the designed joint loss can simultaneously promote "single-axis tracking accuracy improvement" and "multi-axis synchronization deviation suppression". In addition, the comprehensive loss decreased from 0.118 to 0.028, which is consistent with the downward direction of the two types of errors, indicating that there is no bias risk of "optimizing only one item at the expense of the other" in the training process. The marking of improvement rate shows that in the stage of 80~120 rounds, the error decline gradually slows down, and the training enters a stable convergence interval, which conforms to the common law that the depth model changes from rapid fitting to detailed optimization in the later stage.

2.3.3 Offline Training and Online Deployment Process

In the aspect of algorithm implementation, this study carried out the selection of control strategy of "off-line training and on-line reasoning". In the off-line stage, the Transformer model is trained centrally with the help of data sets, and the parameters of the model are continuously optimized by relying on the back propagation algorithm until the model can reach a stable convergence state on the verification set. In the online deployment stage, the trained model is integrated into the control system, and the forward reasoning calculation is carried out, and the corresponding control instructions are generated according to the multi-axis state data collected in real time [15]. In view of the parallel computing characteristics of Transformer model in the reasoning process, its online computing delay can meet the requirements of multi-axis mechanical system for real-time control. By separating off-line and on-line processing, the model training can be more sufficient, and the requirements of real-time and stability concerned in engineering application can also be taken care of.

2.4 Comparison of Benchmarks and Evaluation Indicators

2.4.1 Comparison Algorithm

In order to objectively evaluate the performance of the multi-axis mechanical linkage high-precision control algorithm proposed in this study in terms of effectiveness and advancement, three basic principles should be followed when comparing the algorithms: first, the selected algorithm should have a wide application foundation in the field of multi-axis linkage control; Second, the algorithm itself should reflect the significant differences between different control ideas; Thirdly, the algorithm should be feasible under the same simulation environment and data conditions [16]. The representative control methods selected are as follows:

Proportional-integral-differential control: PID control algorithm. PID control has the advantages of simple structure and intuitive parameter adjustment process, and is widely used in industrial multi-axis systems.

When faced with strong coupling and nonlinear working conditions, its control performance is easily limited.

Cross-coupling control: CCC algorithm. CCC algorithm will improve the performance of multi-axis coordination by introducing synchronization error compensation term between axes, which is representative in the field of multi-axis CNC system.

Control strategy based on neural network: Although this method can fit the nonlinear characteristics of the system to a certain extent, it often depends on local time information, and it is easy to have limitations in modeling ability when dealing with long-term dependence.

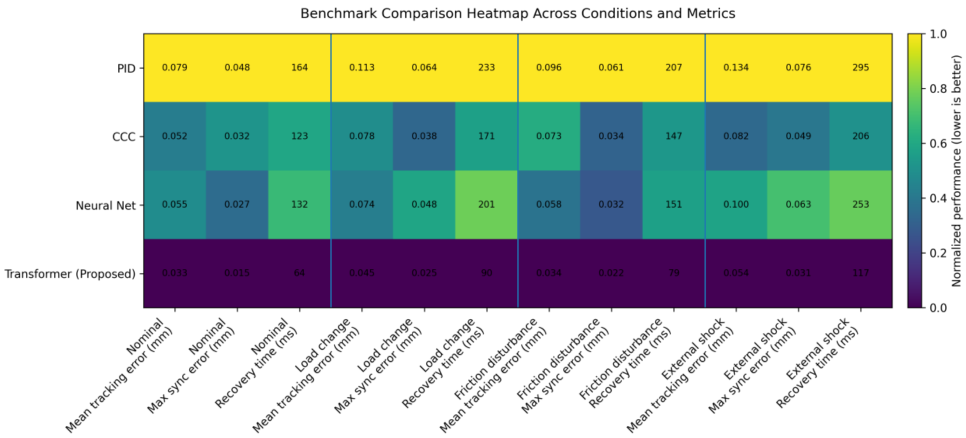

Figure 3: Normalized performance heat map of multi-axis linkage control comparison algorithm under different working conditions and indexes

As shown in Figure 3, the normalized performance of different control methods under diversified operating conditions is compared. The objects of comparison include classical PID control, CCC, control method based on neural network, and Transformer control algorithm proposed in this study. The heat map is normalized by columns, and the evaluation principle of "the smaller the value, the better the performance" is followed. The more biased the cell with cool color, the better the relative performance of the corresponding algorithm is. From the thermal diagram, it can be observed that the Transformer method proposed in this study presents low normalized values in most working conditions and indexes, which shows that the method can maintain good robust control performance and multi-axis coordination ability under the condition of dynamic change of external conditions and strong uncertainty. Although the synchronization error performance of CCC is better than that of traditional PID control on the whole, the recovery time will still be relatively long in the scene disturbed by strong disturbance, which reflects that this method mainly relies on the online error compensation strategy and fails to deeply model and utilize the system timing dynamics. The control method based on neural network can show certain performance advantages under nominal operating conditions. When the operating conditions change significantly, its performance will fluctuate obviously, which shows that its adaptability to the changes of operating conditions outside the distribution of training data still has certain limitations.

2.4.2 Performance Indicators

In order to comprehensively and quantitatively evaluate the performance of various control algorithms in multi-axis mechanical linkage system, a systematic performance evaluation index system is established by virtue of trajectory tracking accuracy, synchronous control performance, system stability and real-time performance [17]. Specific evaluation performance indicators are as follows:

Trajectory tracking accuracy: Evaluate by calculating the deviation between the actual trajectory and the expected trajectory of each motion axis. In order to reflect the control accuracy of the algorithm in both the steady state and the dynamic state, the average absolute error and the maximum tracking error are selected as the specific criteria in this study.

Synchronous controllability: evaluate the coordination and consistency between axes in the process of coordinated motion of multi-axis system. In this study, the maximum synchronization error and the average synchronization error are selected as key indicators, focusing on the suppression effect of the control algorithm on the inter-axis deviation when dealing with complex motion trajectories and high-speed running conditions.

System stability: mainly depends on the smoothness of the control output and the convergence characteristics of the error with time. If the fluctuation amplitude of the control quantity is kept small and the error can quickly converge to a stable level, it shows that the system has good stability and robustness.

Calculation time of control algorithm: by counting the average calculation delay of the algorithm in a single control cycle, it is evaluated whether it can meet the demand of multi-axis mechanical system for real-time control.

With the multi-dimensional performance index system established above, this study systematically and comprehensively evaluates various control algorithms around several key dimensions such as accuracy, synchronization performance, stability and real-time. It lays a unified and objective evaluation foundation for the subsequent simulation experiment results analysis and algorithm comparison.

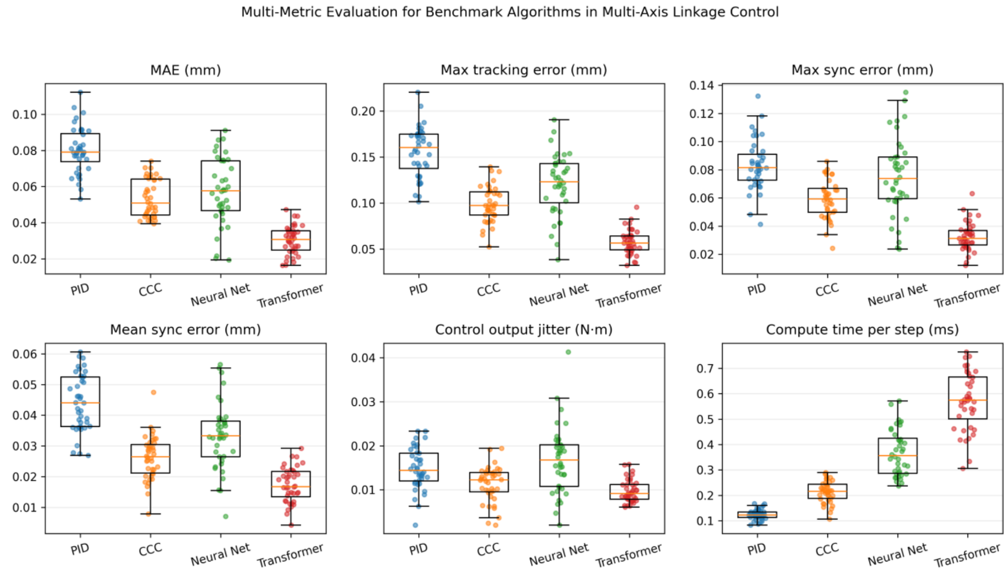

Figure 4: Comprehensive distribution comparison box diagram of comparison algorithm under multi-dimensional performance index system

As shown in Figure 4, the comprehensive performance of four kinds of comparison algorithms, such as PID, CCC, neural network control and Transformer, in the multi-dimensional performance index system is systematically evaluated by combining the box diagram with the jitter scatter diagram. The overall distribution of Transformer is more inclined to the low value range in error correlation, and the range of box is more compact, which shows that this method has higher control accuracy and consistency under different working conditions or trajectories. Compared with PID, CCC has achieved significant improvement in synchronization error, but there is still an obvious trend of error outlier when encountering extreme disturbance conditions. The neural network method shows some advantages in some indexes, but the scattered points are scattered, which reflects its high sensitivity to the change of working conditions and the risk of fluctuation in stability. In terms of real-time, PID has the smallest calculation delay, while the delay of Transformer is relatively high, but it is still within the allowable range of millisecond control cycle.

3. Results and Discussion

3.1 Simulation Experiment Results and Analysis

3.1.1 Simulation Environment Settings

In order to verify the feasibility and effectiveness of multi-axis mechanical linkage high-precision control algorithm based on Transformer model, this study uses MATLAB/Simulink platform to build a simulation experiment environment. The typical three-axis linkage mechanical system is selected as the control object in the experiment. The dynamic parameters of each axis refer to the conventional configuration setting of industrial servo drive system, and the sampling period of the system is set to 1 millisecond to meet the requirements of high-precision control for time resolution [18]. In the simulation process, all the algorithms involved in the comparison run under unified system parameters, initial conditions and reference trajectories, ensuring the fairness and comparability of experimental results.

In this study, the Transformer model outperforms the Long Short-Term Memory (LSTM) network in terms of its ability to capture long-term dependencies and handle complex, dynamic behaviors in multi-axis control. While LSTM networks excel at modeling sequential data, they are inherently limited by their difficulty in capturing global dependencies across multiple axes in multi-axis systems. The Transformer model, with its self-attention mechanism, allows for better global feature extraction, enabling it to model the interrelationships between axes more effectively, especially in the presence of non-linearities and disturbances. Compared to LSTM, which processes sequences in a step-by-step manner, the Transformer model can simultaneously attend to all parts of the sequence, leading to improved synchronization and trajectory tracking performance. The simulation results demonstrate that the Transformer model consistently provides more accurate and stable control, particularly under dynamic and non-linear conditions, thus proving its superior capability for multi-axis linkage control.

In the design of reference trajectory, this study chooses a compound trajectory form which includes acceleration, uniform speed and deceleration stages. With this kind of trajectory, the system will experience obvious dynamic changes in the simulation operation, which can effectively test the response performance of the control algorithm under unsteady working conditions. In order to be closer to the actual engineering application scene, external factors such as friction disturbance and parameter uncertainty are introduced to simulate the complex interference faced by mechanical systems in real operating environment. For all the algorithms involved in the comparison, the control parameters are adjusted one by one through the preliminary experiments to ensure that each algorithm can achieve better control effect and avoid unnecessary performance deviation caused by improper parameter setting.

In the simulation, the system records the displacement data, velocity data and corresponding control input variables of each motion axis in real time, and synchronously calculates and saves the synchronization error data between axes, which provides the necessary basis for the subsequent trajectory tracking performance analysis, synchronization control effect evaluation and system robustness test.

3.1.2 Trajectory Tracking Performance Comparison

Trajectory tracking performance is a key index to measure the effectiveness of multi-axis mechanical linkage control algorithm. In order to investigate the performance differences between different control strategies, this study compares and analyzes the performance of the control algorithm based on Transformer, the traditional PID control algorithm and the cross-coupling control algorithm in trajectory tracking under the same reference trajectory [19]. The simulation results show that when the system is in the startup stage and the dynamic range where the trajectory changes significantly, all the control algorithms involved in the comparison will have some tracking errors. However, there are obvious differences among different algorithms in the control ability of error amplitude and the time required to converge to steady state.

Under the same reference trajectory conditions, the traditional PID control algorithm can realize the basic trajectory tracking function after the system operation enters the steady state stage. When the system enters the dynamic process of acceleration and deceleration, the fluctuation range of tracking error presented by this algorithm will increase obviously, and it will take a long time for the error to converge to a stable state. Cross-coupling control algorithm can improve the coordination of multiple motion axes to a certain extent, but due to the inherent limitations of the algorithm in modeling the nonlinear characteristics of single axis and the dynamic characteristics of time series, it will still produce obvious tracking errors when the system experiences transient changes. The control algorithm based on Transformer can effectively predict the future dynamic change trend of the system with the help of the information contained in the historical state sequence of the system, and can generate more reasonable control instructions at the initial stage of trajectory change, so that the tracking error can converge quickly.

Table 3. Comparison of Trajectory Tracking Performance of Different Control Algorithms

control algorithm	Average tracking error (mm)	Maximum tracking error (mm)	Steady state error (mm)
PID control	0.084	0.152	0.041
Cross coupling control	0.056	0.098	0.028
Transformer control	0.031	0.061	0.014

As shown in Table 3, the Transformer control algorithm is obviously superior to the contrast algorithm in terms of average tracking error and maximum error, which shows that this method has obvious advantages in improving the trajectory tracking accuracy of multi-axis systems.

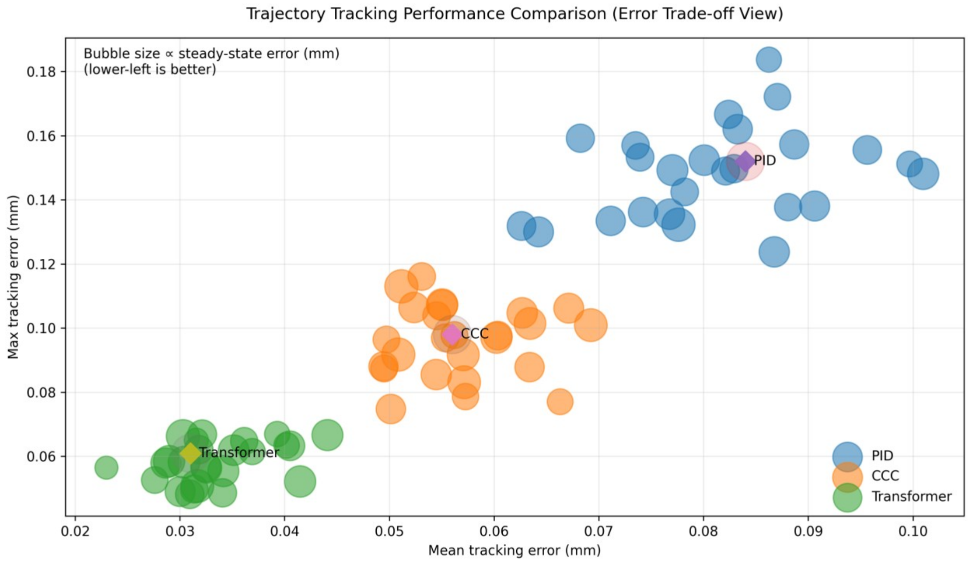

Figure 5: Bubble Scatter Diagram of Trajectory Tracking Error Trade-off Relationship of Different Control Algorithms

As shown in Figure 5, the bubble scatter diagram comprehensively compares the performances of PID, CCC and Transformer control in trajectory tracking tasks. The scattered points corresponding to PID are mostly distributed in the upper right area, and the bubbles are generally large, which reflects that the peak error and steady-state error of the control are high in the dynamic stage, highlighting the limitations of traditional control under strong coupling and time-varying conditions. The scattered points of CCC move to the lower left area as a whole, which shows that the tracking quality has been improved by synchronous compensation mechanism, but its distribution still has some discreteness, which means that transient error fluctuation will still occur in the stage of partial disturbance or dramatic change of trajectory. The scattered points corresponding to the Transformer control are concentrated in the lower left area, and the bubbles are obviously smaller and more compact, which shows that this method can not only reduce the average error and the maximum error, but also maintain more stable performance consistency under multiple simulation conditions.

3.1.3 Synchronization Control Performance Analysis

In the multi-axis mechanical linkage system, the synchronization ability between the moving axes will directly affect the running accuracy of the whole system and the final machining effect.

In order to evaluate the performance of different control algorithms in synchronization control, this study mainly analyzes the changing trend of synchronization errors generated by different algorithms in the whole simulation process.

The simulation results show that the traditional PID control algorithm has obvious synchronization error when multiple axes move at the same time because there is no clear inter-axis coordination mechanism, and it often has a large peak value when the system changes dynamically. Cross-coupling control algorithm can effectively reduce the amplitude of synchronization error by introducing inter-axis error compensation mechanism, but its compensation function is mainly based on the error information at the current moment, and the consideration of multi-axis historical dynamic correlation is still insufficient. Transformer control algorithm builds the overall model of multi-axis state sequence with the help of self-attention mechanism, and can comprehensively consider the historical motion information of multi-axis in the control decision-making stage, which significantly inhibits the generation of synchronization errors.

Table 4. Performance comparison of different algorithms under synchronization error and disturbance conditions

Control algorithm	Average synchronization error (mm)	Maximum synchronization error (mm)	Recovery time after disturbance (ms)
PID control	0.047	0.092	180
Cross coupling control	0.031	0.061	120
Transformer control	0.016	0.034	65

As shown in Table 4, the Transformer control algorithm has obvious advantages in synchronous control performance, and can realize multi-axis coordinated motion with higher precision.

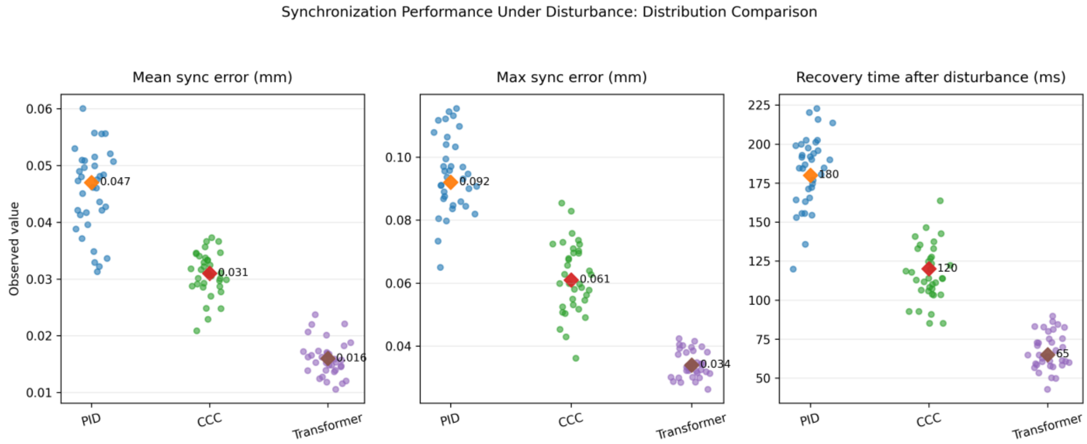

Figure 6: Comparison diagram of synchronization error and recovery time distribution of different control algorithms under disturbance conditions

As shown in Figure 6, the synchronization control performance of PID control, CCC control and Transformer control under disturbance conditions is compared and analyzed by using the scatter distribution diagram of bee colony style. The left, middle and right panels correspond to three key indicators: average synchronization error, maximum synchronization error and recovery time after disturbance. For each algorithm, discrete point clouds are generated by multiple simulation results, which reflect the fluctuation of the performance of the algorithm in different disturbance intensities and trajectory segments, and the index center values given in Table 4 are marked with diamond points. It can be observed from the figure that the whole point cloud of PID algorithm is located in a higher numerical range, and its distribution is more dispersed, which indicates that the algorithm lacks a clear inter-axis coordination mechanism, and its synchronization deviation will be more easily amplified and produce a larger peak when facing dynamic changes, and the required recovery time will be longer. Compared with PID, the synchronization error of CCC algorithm shows an obvious downward trend, and the central position of its point cloud is lower and more concentrated, which shows that the inter-axis error compensation mechanism can improve the synchronization performance, but its performance is still discrete under strong disturbance conditions. The point cloud of Transformer algorithm shows a significant downward shift in all three indicators, and the distribution is the most compact, with outstanding advantages in maximum synchronization error and recovery time. It shows that the algorithm can form a reasonable control decision more quickly after the disturbance by using the historical sequence information to model the coupling dynamics between multiple axes, thus effectively restraining the synchronization error and accelerating the recovery process of the system.

3.1.4 Robustness and Anti-disturbance Test

In order to investigate the adaptability of different algorithms in complex operating environment, external disturbances, such as random load changes and sudden disturbance torque, are deliberately added in the simulation process to evaluate the robustness of different control strategies. The disturbance application system enters the stable operation stage, the purpose of which is to focus on observing the error changes and subsequent recovery process of the system after being disturbed.

The simulation results show that when the system is affected by disturbance, the error generated by PID control algorithm will increase rapidly, and its recovery process will be relatively slow, and there will be obvious overshoot [20]. Cross-coupling control algorithm shows some advantages in restraining disturbance, but when the disturbance intensity is large, the synchronization error of the algorithm will still expand. Transformer control algorithm can learn the dynamic response characteristics of the system under the disturbance condition with the help of historical data, so the control output can be adjusted immediately after the disturbance occurs, and the system state can return to the vicinity of the stable trajectory quickly.

3.2 Discussion

3.2.1 Algorithm Advantages and Mechanism Analysis

Based on the simulation results, the advantages of the algorithm are deeply analyzed at the level of control mechanism. Transformer model, with its self-attention mechanism, realizes the overall modeling of the historical state of multi-axis system, and the control decision is no longer only dependent on the local error information at the current moment, but also can consider the dynamic change trend of the system in the time dimension. This is helpful to predict the trend in the early stage of system dynamic change, so as to generate more reasonable control instructions earlier [21]. The multi-head attention structure enables the model to focus on the key features of different axes and different time scales in parallel, and effectively capture the coupling relationship between multiple axes. Compared with the traditional explicit compensation method, the implicit coupling modeling method has higher flexibility and adaptability, which is also the main reason for the obvious improvement of the synchronization control performance of the algorithm.

3.2.2 Analysis of Parameter Sensitivity, Real-time Performance and Calculation Burden

In practical engineering applications, besides the control effect, the parameter sensitivity and real-time running ability of the control algorithm are also important considerations. According to the simulation results, the Transformer control algorithm does show some sensitivity to the structural parameters such as the number of network layers and the number of attention heads. When the parameters are in a reasonable range, the change trend of control performance is relatively flat, which shows that the algorithm has good parameter robustness. In terms of real-time, the Transformer model adopts parallel computing architecture in the reasoning process, and its online computing delay mainly depends on the forward propagation process. The simulation test results show that under the current system scale, the time required for single-step reasoning can meet the requirements of millisecond control cycle, and will not have a significant impact on the real-time operation of the system. Although the computational complexity of the algorithm is higher than that of the traditional PID control method, it is still feasible to be implemented in engineering with the support of modern embedded computing platform.

3.2.3 Discussion on Limitation and Universality

Although the control algorithm in this study has achieved good performance in the simulation environment, it still has limitations. The effect of the algorithm will be greatly affected by the quality and coverage of the training data. If the actual system operating conditions exceed the distribution range contained in the training data, the control effect may decline to some extent. The structure of the Transformer model itself is relatively complex, and the demand for hardware computing resources will be higher; When deployed in a control system with limited computing resources, further optimization is needed. From the general point of view, the control framework constructed in this study has good expansibility, which can be extended to mechanical systems with different axes or different structural types by adjusting the dimension of input features and making appropriate adaptation to the network structure. In the specific application, it is still necessary to design the target system according to its specific characteristics [22].

3.2.4 Comparison and Extension with Existing Advanced Methods

Compared with the current control methods that mainly rely on neural network or reinforcement learning, the algorithm in this study has obvious advantages in time series modeling and multi-axis coupling feature extraction. Compared with the method that only uses the current state or short-term historical information, the Transformer model can effectively model long-time series data and achieve more stable control effect in complex dynamic environment [23]. The high-precision control algorithm of multi-axis mechanical linkage based on Transformer in this study shows good comprehensive performance in many aspects, such as trajectory tracking accuracy, synchronization performance and robustness, which provides valuable research reference for the practical application of intelligent control methods in multi-axis mechanical systems.

4. Conclusions

Aiming at the key problems in the process of high-precision motion control of multi-axis mechanical linkage system, such as difficulty in modeling, complex coupling relationship between axes and difficulty in balancing control accuracy and synchronization performance, this paper studies the high-precision control algorithm of multi-axis mechanical linkage based on Transformer model. Facing the limitation of traditional control methods in complex nonlinear and time-varying working conditions, the idea of data-driven is introduced, and the advanced deep learning model is combined with multi-axis motion control to explore a new control strategy design path.

During the research, the dynamic characteristics and high-precision control requirements of multi-axis mechanical linkage system are deeply analyzed, and based on the relevant data collected in the actual operation of the system, a set of data sets suitable for time series modeling is constructed. Based on this, a Transformer network architecture for multi-axis control tasks is designed, which processes multiple historical state sequences of multi-axis by means of self-attention mechanism, thus realizing global feature extraction and effectively completing the modeling of system dynamic characteristics and coupling relationship between axes [24]. Through the reasonable configuration of input coding mode, decoding structure of control output and training strategy, the model can successfully output high-precision multi-axis coordinated motion control instructions on the premise of ensuring the stability of the control system.

The simulation results show that compared with the traditional PID control method and cross-coupling control method, the new control algorithm based on Transformer model can improve the tracking accuracy of motion trajectory more effectively, maintain the performance of synchronous control in a good state, and it also has strong anti-disturbance ability. Under the complex working conditions with strong nonlinear trajectory changes or when there are various types of disturbance inputs outside the system, the algorithm can suppress the errors more quickly by virtue of the global sequence modeling mechanism, and promote the system to return to a stable running state [25]. These actual performances verify the full effectiveness and good system robustness of the algorithm under changeable and complex working conditions. The results of in-depth analysis based on experiments show that the research algorithm can meet the basic technical requirements of multi-axis mechanical operation system for real-time response under the premise of using reasonable network structure scale and parameter configuration scheme, which shows that it is feasible to be applied in specific engineering tasks.

Although some achievements have been made in this study, there are still some shortcomings that need to be improved. For example, the performance of the algorithm depends on the coverage of the training data on the system working conditions to a certain extent. If the system operating conditions change greatly, the generalization ability of the model itself still needs to be improved; The structure of Transformer model itself is relatively complex, and it is still difficult to implement when it is deployed in an embedded control system with limited computing resources. The follow-up research work can focus on the lightweight design of the model, online adaptive learning mechanism and the integration with classical control methods, so as to effectively enhance the practicability of the algorithm in engineering practice and expand its application scope.

The results of this study provide a valuable technical path attempt for the Transformer model in the special field of multi-axis mechanical linkage for high-precision control, and bring corresponding theoretical guidance and reference significance in engineering implementation to promote the deeper application of control methods with intelligent characteristics in high-end equipment manufacturing and automation systems.

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