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A survey of offline precision calibration of industrial robots

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Abstract. As the need for precision and efficiency grows in industrial manufacturing, the accuracy of industrial robots assumes paramount importance. Nevertheless, factors, such as mechanical structures and assembly processes often introduce errors, compromising robots' positioning and repeatability accuracy. Consequently, precise calibration and compensation of these errors are paramount for optimizing robots' performance. A thorough analysis of error sources and the establishment of error models in industrial robots are conducted in the present study, with special attention paid to offline calibration methods. This paper reviews the robot error model building methods and offline accuracy calibration techniques, summarizes the technical difficulties of the calibration task, and proposes the future development direction for the difficulties such as the complexity of error modeling, the difficulty of non-motor calibration calculation, and the traditional stiffness compensation that does not meet the needs of the robot's operation process. The importance of this research lies in its potential to improve the accuracy and reliability of industrial robots, thus contributing to the development of industrial automation.

Keywords: industrial robots, offline accuracy calibration, error modeling, accuracy improvement, industrial automation.

1. Introduction

With the continuous progress of industrial manufacturing technology, industrial robots have become a key element in the production line, and their accuracy and stability are crucial for enhancing production efficiency, reducing costs and improving product quality. However, due to a variety of factors such as mechanical structure, assembly process and working environment, there are errors in the operation of industrial robots, that directly affect the positioning and repositioning accuracy, thus threatening production stability and product quality. Therefore, accurate calibration and compensation of industrial robot errors have become important research directions to improve performance.

The motion errors of industrial robots come from complex and varied sources, which interfere with the robot's motion trajectory and the positioning accuracy of the end-effector. The basis of error calibration and compensation is to analyze the causes of error deeply and establish the corresponding model. The calibration methods are mainly divided into two categories: online calibration is highly accurate but complicated and easy to interfere with the operation of the robot, while offline calibration is simple and efficient without interfering with normal production, so it is more popular in practical applications.

This paper first introduces the sources and classification of industrial robot errors, and then focuses on the establishment method of the error model and the realization process of the offline calibration method. Finally, this paper summarizes the advantages and disadvantages of the existing offline

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calibration methods and looks forward to the future development trend, with a view to providing new ideas and methods to promote the accuracy improvement and performance optimization of industrial robots.

2. Robot errors sources and modeling

2.1. Industrial robot positioning accuracy

Robot positioning accuracy refers to the difference between the actual position and the target position, and is divided into the absolute positioning accuracy and the repeated positioning accuracy. The former measures the ability to localize to the target position at the end of the robot without a reference point, while the latter focuses on the coincidence of multiple attempts to reach the same position. Both of them have a direct impact on the operational efficiency and stability of the robot, so accurate measurement, in-depth analysis and effective control are crucial.

Currently, the repeated positioning accuracy of industrial robots has reached the high precision level of 0.1mm, but the absolute positioning accuracy is often lower than this. This difference mainly stems from the deviation between the nominal parameters and the actual parameters, including structural design, manufacturing, operation process, measuring components and external environment and other influencing factors. Errors can be divided into geometric parameters and non-geometric errors.

Methods to improve positioning accuracy, such as enhancing stiffness and improving machining and assembly accuracy, are effective but costly, and the error may increase after long-term operation due to mechanical wear or load changes. Therefore, the method of identifying the structural parameters of the robot and constructing a mathematical model is more commonly used in practical applications, where the deviation of the structural parameters is identified and the kinematic compensation is performed to improve the absolute attitude and positional accuracy by measuring the end attitude and positional errors. Choosing a suitable kinematic description model is crucial to obtain ideal error identification results.

2.2. Robot kinematics modeling

The kinematic model of the robot is the basis for constructing the motion error model, and its parameter calibration results can correct the model and improve the motion accuracy. The model needs to meet the requirements of completeness, continuity and parameter minimization. The D-H (Denavit-Hartenberg) models proposed by Denavit [1] and Hartenberg [2] describe the spatial coordinate localization of a single joint with four parameters, which is concise and physically meaningful, and is widely used in robot control and trajectory planning. However, the DH model has continuity and description ambiguity problems in singular points and tree and closed-chain rod systems [3]. The MD-H model proposed by Hayati et al. [4] introduces a rotation parameter around the y-axis and moves the axis system to establish the position, which solves these problems and ensures parameter minimization and model accuracy.

The S-model proposed by Stone et al. [5] increases the kinematic parameters representing the rotational and translational spatial transformations to obtain a 6-parameter model for a single rod, and the model can flexibly determine the origin and direction of the coordinate system of the connecting rod. The CPC model proposed by Zhuang and Roth et al. [6] extend the axial and axial positional parameters of the DH-model to three parameters, respectively, and obtain 6n descriptive parameters for the n-rods, thus solving the problems of discontinuity and singularity, but too many parameters also cause the redundancy of parameters and the problem of increased computation and accuracy of model identification correction.

In the 1980s, Brockett [7] proposed an exponential product model (POE) based on spinor theory, which describes the joint coordinate system localization with 6 parameters, which is singularity-free but does not satisfy the principle of minimum parameters [8]. Under the minimum linear representation in Euclidean space, 4 parameters can completely describe the adjacent link coordinate system position and attitude. Yang et al. [9] proposed a minimalized POE model, which reduces the degrees of freedom of each joint axis to 4, with no parameter redundancy, and reduces the amount of computation.

Quaternions extend the concept of complex numbers and can represent three-dimensional spatial rotations, avoiding the robot singularity problem. Dantam et al. [10] proposed a dyadic quaternion model, which is fast and does not fall into singularities, but constructing a complex model and algorithmic structure increases the difficulty of application.

2.3. Industrial robot rigid model

Industrial robot end errors mainly come from joint angle deviation and linkage parameter deviation [11]. Non-joint factors such as elastic deformation, backlash and thermal deformation can lead to linkage parameter deviation, which affects the end position accuracy. During heavy or large load operations, the flexible deformation of each joint leads to a decrease in end motion accuracy. Therefore, the purely rigid rod kinematic model is insufficient, and a dynamic model describing the rigidity of the robot needs to be further proposed. Robot stiffness modeling methods include finite element analysis (FEA), matrix structure analysis (MSA) and virtual joint modelling (VJM).

The finite element analysis method divides the continuous multi-degree-of-freedom object into flexible units, which is convenient for numerical solutions. After the displacement relationship of each unit is established, the dynamics equations can be deduced to reflect the performance of the robot system. Klimchik et al. [12] proposed a CAD model-based stiffness matrix acquisition method, that takes into account the geometry and interaction of the connecting rods and improves the efficiency and accuracy of parameter identification. Liu et al. [13] utilized force and torque duality to construct a Cartesian stiffness matrix, which enables rapid evaluation of the stiffness of the parallel mechanism. Zhao et al. [14] proposed a n(3RRIS) robot stiffness modeling method by combining the virtual joint method and matrix structure analysis method, and proved that increasing drive constraints can improve the stiffness.

The Matrix Structural Analysis (MSA) method examines the robot from a structural mechanics point of view, treating the connecting rods as beam structures and analytically calculating their stiffness matrices in order to understand the mechanical properties of the single rods. For multibar robotic systems, MSA is based on static equilibrium and generalizes the local stiffness matrix to the global one. Klimchik et al. [15] proposed an analytical method for general robotic stiffness matrices, which contains a simplified recursive algorithm to obtain reliable stiffness matrix results. Detert et al. [16] developed a stiffness modeling method based on matrix structural analysis, which especially takes into account the nonlinear stiffness properties and is able to calculate the deformation of the mechanism under load directly. deformation under load.

The virtual joint modeling method defines the joints as virtual springs, constructs the joint rotational stiffness matrix and converts it to a Cartesian stiffness matrix under the precondition of ignoring the deformation of the linkage [17]. A more comprehensive VJM method is proposed by considering joint linkage and transmission mechanism flexibility. Tsumugiwa et al. [18] introduce virtual joints for 7-degree-of-freedom robots to compensate for the linkage flexibility modeling error. Abele et al. [19] enhance the stiffness model by adding bearing tilt stiffness and linkage deformation elements based on the traditional VJM. Klimchik et al. [20] propose a complex elastostatic model by considering gravity force that compensates for the gravity elastic deformation error of heavy robots.

Compared with purely rigid kinematic robot modeling, the above rigid robot modeling approaches are more comprehensive and accurate. They not only consider the effect of joint angle deviation on the end error, but also explore in depth the effect of linkage parameter deviation and non-joint factors such as elastic deformation, tooth backlash and thermal deformation on the robot’s performance. These methods not only improve the end-motion accuracy of robots during heavy and large load operations, but also lay a solid foundation for further development in the field of robotics.

3. Off-line error calibration methods

To improve the positioning accuracy of industrial robots, geometric and non-geometric error calibration techniques need to be deeply applied. This technology eliminates manufacturing and assembly errors through precise measurements and algorithms that adjust parameters to meet application requirements. Offline calibration pre-measures errors and improves accuracy with compensation algorithms. Scholars have extensively researched and proposed a variety of methods to improve accuracy, and have achieved remarkable results.

Offline calibration aims to construct a kinematic error model of the robot by measuring the end positioning errors under multiple joint configurations in the robot's workspace. The robot's errors in kinematic parameters are identified, or the robot's error mapping relationships in Cartesian space or joint space are established. The acquired error model or error mapping is integrated into the robot's compensation algorithm, aiming at realizing the accurate prediction and effective compensation of the target point localization error, so as to further improve the robot's localization accuracy, and ensure that the robot can achieve a higher degree of accuracy when performing tasks. At present, the common offline calibration methods include kinematic calibration and non-kinematic calibration.

3.1. Kinematic calibration

Kinematic calibration uses a robot kinematic model for error modeling and compensates for accuracy through offline calibration. The process includes measuring the motion error, constructing an accurate error model, identifying the structural parameter error, and correcting the relevant parameters to make the robot setup parameters more realistic.

Robot error identification can be regarded as a numerical estimation problem, and the least squares method is often applied to robot error identification due to the simplicity of the solution, but the least squares method is prone to misalignment when the identification matrix is close to the singularity, so there are a number of improvements to the least squares method proposed in the field of robot kinematics calibration [21-24]. In addition to the least squares method, methods such as extended the Kalman filter [25], great likelihood estimation [26], genetic algorithms [27], and artificial neural networks [28-29] can also be used to solve the problem of robot kinematic parameter identification.

Error compensation is a key step after error identification. Gao et al. [30] used singular value decomposition to separate redundant parameters and improved the least squares method for parameter identification. Messay et al. [31] constructed a non-redundant and non-singular simplified DH model and proposed to re-simplify the model to achieve kinematic calibration. These methods require a highly open robot control system and its modification, which is costly. Therefore, industrial robot geometric error compensation is often aimed at the joint space, the error is brought into the theoretical model to correct the parameters, which are then transformed to the joint space by an inverse solution, and the robot motion is controlled to complete the compensation. Mustafa et al. [32] utilized the exponential product model and laser tracker calibration to compensate for the amount of angular motion, and Russell et al. [33] calibrated the kinematic parameters of the joint space to improve the localization accuracy. Another part of scholars based on the idea of differential transformation, where the robot's localization error is regarded as a small displacement, and they construct the differential transformation of the rotation amount of each joint axis to represent it. This method is also called the differential error compensation method [34-35].

3.2. Rigidity calibration

Poor stiffness performance is an important factor contributing to the low machining accuracy of industrial robots, and being able to accurately recognize the joint stiffness and end Cartesian stiffness of a robot has an important impact on improving robot accuracy.

3.2.1. Joint stiffness. The main source of non-geometric errors is at the joints [10], so accurate measurement of joint stiffness is of significant importance for optimizing robot stiffness through compensation or attitude adjustment. Robot joint stiffness is usually considered a constant by assuming it is a torsion spring. Nubiola et al. [36] introduced four flexibility parameters for the middle four axes of a 6R robot and performed a least-squares parameter calibration in unison with all the parameters of the MDH model to improve the kinematic accuracy to 0.3 mm. Zhu et al. [37] adjusted the robot's end loads and observed the joints using a laser tracking device. The small changes in the measurement points on the connecting rod were used to accurately measure the joint deformation. Combined with the force sensor data, structural analysis was used to derive the joint torque changes and determine the static stiffness of the joints at specific Cartesian space positions. Based on the stiffness identification results of different joint positions, a polynomial fitting is used to construct a joint stiffness variation model, and the Jacobi matrix and conservative congruence transform are combined to predict the Cartesian stiffness of the robot. Filion et al. [38] compensated the structural parameters and joint stiffness coefficients obtained from the identification in static configurations and no-load conditions back to the robot's controller, and a better compensation effect was achieved. Jiao et al. [39] proposed a spatial grid-based regular sampling method. Jiao et al. proposed a regular sampling point selection method based on a spatial grid, and combined with the Levenberg-Marquardt kinematic parameter calibration and static joint stiffness identification methods, a comprehensive identification method was proposed to realize the simultaneous identification of robot kinematic and stiffness parameters. Based on the results of different workspaces, a variable-parameter stiffness model is established and a model-based online external load sensing error prediction and compensation method is proposed. Cen et al. [40] proposed an innovative joint stiffness identification method for robots by using a laser displacement sensor to identify the joint stiffness, and the coupling effect between linear displacement and rotational displacement is taken into account.

3.2.2. Cartesian stiffness. The Cartesian stiffness of a robot is the stiffness in the workspace at the end of the robot. Yang et al. [41] measured the stiffness by tightening up all but one of the joints in order to measure their stiffness, and completed the stiffness measurements by repeating this operation for each joint. Thus, as long as the stiffness of the connecting rod is known, only six measurements are needed to obtain the Cartesian stiffness matrix for the entire Cartesian workspace of the robot. The drawback of this method is that only the stiffness of the joints is considered, and the deformation of the connecting rods is neglected. Therefore, Lin et al. [42] integrated the deformation caused by the flexibility of the joints and connecting rods along all axes, used the measurement of the displacement of the robot's end-effector under a certain load and interpolated it to obtain the Cartesian stiffness matrix of the robot in the complete workspace. Further, considering the end-loaded machining mechanism, Slavkovic et al. [43] designed a G-code-based robot controller, that combines the accurate prediction of cutting force and static tip displacement by the constructed robot flexibility and mechanical model, and further optimizes the trajectory of the robotic arm at the G-code level, which improves the offline compensation accuracy and ensures the accuracy and stability of the robot operation.

Although the above robot kinematic and stiffness accuracy calibration techniques can effectively identify the robot's kinematic and stiffness errors, due to the complexity and mutual coupling of the error sources affecting the robot's localization accuracy, separate kinematic and stiffness calibration cannot completely compensate for the robot's errors. In this regard, Gong et al. [44] studied the effects of geometric error, connecting rod flexibility and temperature variation on robot localization accuracy. They combined the geometric error, position-related flexibility error and time-varying thermal error to construct a comprehensive error model. These errors were inversely corrected using a laser tracker, and with the help of orthogonal regression methods, an empirical thermal error model between the thermal errors of the robot's parameters and the corresponding temperature field was developed, and the results showed that the accuracy of their calibrated robots was improved by an order of magnitude.

3.3. Non-kinematic calibration

In order to cope with the problem of complex coupling of robot errors, researchers are no longer confined to the traditional error model-based calibration method, but instead explore a new idea of non-kinematic calibration. Non-kinematic calibration is a model-free parametric calibration method that focuses on studying the mapping relationship between robot end positioning errors and joint angles. This method collects a large amount of end Cartesian coordinate accuracy information and combines it with the distribution law of motion error in space, and utilizes motion bias to compensate for the motion error, ultimately realizing the accuracy improvement.

Zeng et al. [45] proposed the concept of error similarity and pointed out that when the inputs of each joint of the robot are similar, the corresponding localization errors are similar, and the mapping relationship between localization error and joint angle is established by the variational function analysis method, which can be used to predict the localization error of the target point. In addition, a linear unbiased optimal estimation strategy with error post-processing is adopted to compensate for the localization error without modifying the robot control parameters. Cai et al. [46] decompose the localization error into deterministic drift and residual part based on the error similarity, and determine the drift and compensate the error through the generalized Kriging method of modeling the error of industrial robots, and the experimental results show that this method can effectively improve the compensation accuracy.

The above method examines the error mapping relationship in the workspace based on error similarity to realize the estimation and compensation of target position localization error, therefore, the work can be regarded as a numerical estimation problem. Neural networks are capable of self-learning, self-adaptation and high error tolerance for a large number of data patterns, therefore, neural networks are also widely used in the construction of mapping relationships between end position error and joint angle. Takanashi [47] used neural networks and an inverse kinematics computation module in parallel to learn the robot model error and compensate the output through neural networks, and the experimental results showed that the absolute positioning error of the robot was significantly reduced. Wang et al. found that [48-49] based on the neural network algorithm, by obtaining the position error of each point in the calibration space and constructing the training data set, the neural network model is used to approximate the error surface for compensation, which improves the calibration accuracy compared with the traditional linear interpolation method. Although the above non-kinematic calibration technique overcomes the disadvantage of complex modeling of robot error models, the method of integrating all the errors in the end representation neglects the study of the distribution law between various errors within the robot, and the non-kinematic calibration method, as a numerical estimation means, often depends on the expansion of the amount of data for the improvement of its calibration accuracy.

4. Conclusion

Highly accurate operational performance is the prerequisite for more accurate and intelligent applications of robots in manufacturing, and the construction of accurate error models and the application of offline calibration methods are key means to achieve this goal. Error modeling helps to understand and predict errors in robot motion, while offline calibration ensures that robot excellent performance is maintained over long periods of time through high-precision measurements and corrections. It cannot be ignored that the complex modeling challenges of kinematic and stiffness calibration methods, as well as the tendency of non-kinematic calibration methods to fall into local optimal solutions and heavy computational burdens, are evident when dealing with the tedious calibration tasks in machining. These problems often lead to inaccuracies in the calibration model, a significant increase in the measurement cost, a lack of adaptability to industrial production environments, and inefficiencies in the parameter identification and error compensation algorithms. As a result, the end-of-arm accuracy of the robot after correction of the calibration results is often difficult to meet the stringent requirements of machining accuracy. Most of the studies on the stiffness compensation strategy of robots are on the stiffness compensation of fixed working postures, and there is a lack of research on the dynamic stiffness effect caused by posture changes in the trajectory.

Therefore, for robot error modeling, it is necessary to explore the error propagation mechanism in depth, decouple the coupling parameters of the error model, and precisely separate the error sources in order to construct a more accurate and efficient model. In the process of non-kinematic calibration, the error sources should be analyzed in depth to ensure accuracy, while taking into account the distribution characteristics of the error data in space. The optimization of the calibration algorithm by integrating intelligent algorithms aims to accelerate the convergence process and thus design a more efficient calibration strategy. For the dynamic stiffness of the robot operation, the impact of stiffness change on operation performance should be studied, and the real-time stiffness monitoring and compensation technology should be developed to ensure the accuracy and stability of the robot operation.

Overall, the research on precision calibration of robots makes the operation accuracy of industrial robots continue to improve, and by combining advanced algorithms and sensor technology, the offline precision calibration methods will develop in the direction of more intelligence and automation to further enhance the performance of industrial robots.

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