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Sensitivity analysis of geometric parameter errors for industrial robots based on random forest*

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***Abstract*—Geometric parameter errors have a direct impact on the positioning accuracy of industrial robots, making their reduction crucial for enhancing accuracy. Identifying the key geometric parameter errors with the greatest impact on robot accuracy significantly improves its performance. In this paper, we estimate the impact of geometric parameter errors in industrial robots on position accuracy using sensitivity analysis with the Random Forest (RF) method. Firstly, the kinematic error model of the industrial robot is constructed based on the MD-H convention. The principle of RF method is presented, and the geometric parameter errors are randomly sampled by the Latin hypercube sampling (LHS) method, the predictor delta importance (PDI) of each geometric parameter error is calculated. Then, the influence of each geometric parameter error on the position accuracy of the same pose is analyzed. Finally, a simulation experiment is performed with a 6-DOF industrial robot to validate the proposed method's correctness and effectiveness. The results indicate that the precision design of the vital geometric parameter errors could significantly enhance the position accuracy of the industrial robot.**

I. INTRODUCTION

Because of its flexibility, intelligence and versatility, industrial robots are used in many industrial manufacturing fields. Due to the manufacturing errors, assembly errors, motion control errors, and other factors of the core components of industrial robots, geometric parameter errors may occur in industrial robots[1]. Geometric parameter errors in industrial robots result in deviations between nominal and actual position and orientation, leading to a failure to meet high-precision requirements. Therefore, improving position accuracy in industrial robots is of significant importance.

To enhance the position and orientation accuracy of industrial robots, reducing geometric parameter errors in the design, processing, and assembly stages is crucial[2, 3]. Each geometric parameter error of an industrial robot has a unique impact on position and orientation accuracy. To enhance the position and orientation accuracy quickly and effectively, and avoid the blindness of error compensation, sensitivity analysis of geometric parameter errors is usually required.

Sensitivity analysis methods are mainly divided into two categories: local sensitivity analysis and global sensitivity analysis[4, 5]. The common methods of local sensitivity analysis include partial differential method[6] and space vector projection method[7]. The local sensitivity analysis method is performed to assess the sensitivity of the geometric parameter errors of industrial robots in the above methods. This simple yet effective method is particularly suitable for linear models. However, only the influence of a single geometric parameter error on the pose error could be analyzed. The interval range of geometric parameter errors cannot be too large. The local sensitivity analysis method is not suitable for the nonlinear kinematic error model of industrial robots.

The global sensitivity analysis method effectively addresses the limitations of local sensitivity analysis, making it applicable to both linear and nonlinear models. The interval range of geometric parameter errors can be extended to its entire domain of definition. The sensitive coefficients of all geometric parameter errors can be calculated simultaneously[8, 9]. In this paper, the global sensitivity analysis method based on random forest, aided by the eigenvalue PDI, is employed to analyze the sensitivity of geometric parameter errors in the IRB 2400 6-DOF series robot. The goal is to identify the most influential sources of geometric parameter errors that impact the robot's positioning accuracy. This analysis serves as a crucial foundation for enhancing the absolute position accuracy of industrial robots.

II. KINEMATIC ERROR MODELING OF THE INDUSTRIAL ROBOT

The Denavit-Hartenberg (D-H) convention is commonly utilized in kinematics modeling for industrial robots[10], but it is impossible to express the small rotation between parallel axes. Based on the D-H model, some scholars proposed a MD-H (Modified D-H) kinematic model that includes an angle parameter β around the y axis between the parallel axes to improve the accuracy of the kinematic model. The D-H convention method is introduced firstly.

The homogeneous transformation matrix describes the relationship between adjacent links in the D-H convention. The schematic diagram of two adjacent joints and links is depicted in Fig. 1. Four kinematic parameters are used to locate the $\{i\text{-}1\}$ frame relative to $\{i\}$ frame in the D-H convention. The four geometric parameters could be divided into two categories: link parameters and joint parameters. The link parameters consist of the link length a_{i-1} and link twist angle α_{i-1}. The joint parameters include joint angle θ_i and link offset d_i. The homogenous transformation matrix of two adjacent link frames $\{i\}$ and $\{i\text{-}1\}$ could be expressed as in (1).

$$ {}_{i-1}^{i}\boldsymbol{T} = Rot(x,\alpha_{i-1})Trans(x,a_{i-1})Rot(z,\theta_i)Trans(z,d_i) \quad (1) $$

Where $Rot(\bullet)$ denotes the rotation transformation matrix along the axis and $Trans(\bullet)$ represents the translation transformation matrix around the axis.

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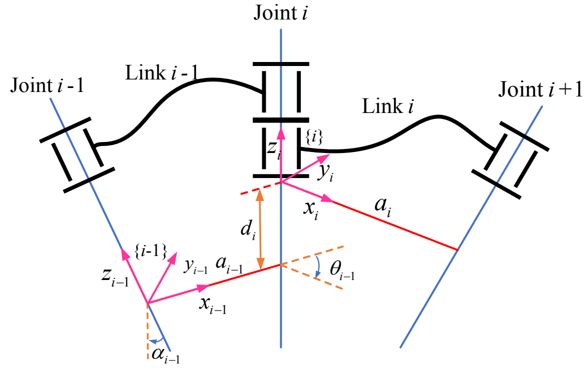

Fig. 1. Two adjacent joints and links in an industrial robot

When axis 2 and axis 3 of an industrial robot are parallel, a singular solution will result. This requires the introduction of an angle parameter β around the y-axis when i is equal to 2, namely, the construction of an MD-H model containing 5 parameters to make up for the defects of the D-H model. When i is equal to 2, the homogeneous transformation matrix between two adjacent link frames can be expressed as:

$$\begin{aligned} {}_{i-1}^{\ \ i}\boldsymbol{T} = Rot(x,\alpha_{i-1})Trans(x,a_{i-1})Rot(z,\theta_i) \\ Trans(z,d_i)Rot\left(y_i,\beta_i\right) \end{aligned} \tag{2}$$

For the industrial robot with six revolute joints shown in Fig. 2, six homogenous transformation matric could be obtained. Thereby, the overall transformation matrix between the robot base frame {0} and the end-effector frame {6} could be described in (3).

$${}_6^0\boldsymbol{T} = {}_1^0\boldsymbol{T}\,{}_2^1\boldsymbol{T}\,{}_3^2\boldsymbol{T}\,{}_4^3\boldsymbol{T}\,{}_5^4\boldsymbol{T}\,{}_6^5\boldsymbol{T} = \prod_{i=1}^{6} {}_{\ \ i}^{i-1}\boldsymbol{T} \tag{3}$$

Assuming that the position of tool center position (TCP) in the end-effector frame are respectively ${}^6\boldsymbol{P}$. Thus, the ideal position ${}^6\boldsymbol{P}_{ideal}$ of the TCP in the robot base frame could be calculated as in (4). Without loss of generality, the value ideal position is defined as ${}^6\boldsymbol{P}_{ideal}$=[0 0 0 1]^T.

$${}^0\boldsymbol{P}_{ideal} = {}_6^0\boldsymbol{T}\,{}^6\boldsymbol{P} \tag{4}$$

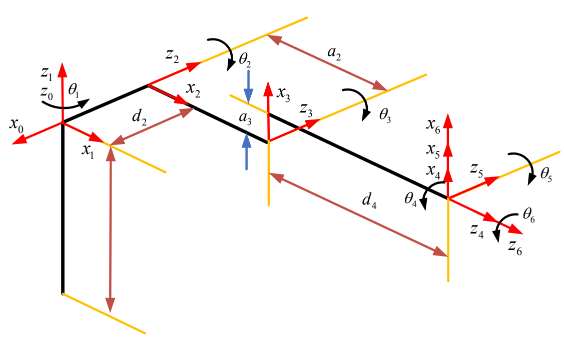

Fig. 2. Structure of the industrial robot with six revolute joints.

Equation (3) is the ideal kinematics model of the industrial robot. Due to the assembly errors and manufacturing errors of the robot, the nominal geometric parameters of the robot will be different from the actual geometric parameters. Assuming that the geometric parameter errors of industrial robots are respectively δa_{i-1}, δd_i, $\delta\alpha_{i-1}$, $\delta\theta_i$, $\delta\beta_i$. The actual homogenous transformation matrix between two adjacent link frames {i} and {i-1} could be expressed as in (5).

$$\begin{aligned} {}_{i-1}^{\ \ i}\boldsymbol{T}_{actual} = Rot(x,\alpha_{i-1}+\delta\alpha_{i-1})Trans(x,a_{i-1}+\delta a_{i-1}) \\ Rot(z,\theta_i+\delta\theta_i)Trans(z,d_i+\delta d_i) \\ Rot\left(y,\beta_i+\delta\beta_i\right) \end{aligned} \tag{5}$$

Thus, the actual transformation matrix between the robot base frame and the end-effector frame could be expressed as in (6).

$${}_6^0\boldsymbol{T}_{actual} = \prod_{i=1}^{6} {}_{\ \ i}^{i-1}\boldsymbol{T}_{actual} \tag{6}$$

Due to the influence of geometrical parameter error factors of industrial robots, the actual position of the TCP in the robot base frame are different from the ideal that of TCP. The actual position ${}^6\boldsymbol{P}_{actual}$ of the TCP in the robot base frame could be computed as follows:

$${}^0\boldsymbol{P}_{actual} = {}_6^0\boldsymbol{T}_{actual}\,{}^6\boldsymbol{P} \tag{7}$$

The positional error of the TCP could be denoted as in (8).

$$\delta\boldsymbol{P} = [e_{px}, e_{py}, e_{pz}]^T = {}^0\boldsymbol{P}_{actual} - {}^0\boldsymbol{P}_{ideal} \tag{8}$$

Where e_{px}, e_{py}, e_{pz} are the positional errors of the end-effector frame along the x, y, and z axes relative to the base frame.

The absolute positional errors could be respectively expressed as in (9).

$$e_p = \left|\delta\boldsymbol{P}\right| = \sqrt{e_{px}^2 + e_{py}^2 + e_{pz}^2} \tag{9}$$

III. Sensitivity Analysis of Geometric Parameter Errors Based on Random Forest

The sensitivity analysis of geometric parameter errors quantifies how each geometric parameter error affects an industrial robot's positional errors. This section uses an RF-based method in the robot's error model to estimate each error's contribution on the positional errors.

A. Latin Hypercube Sampling

Before performing parameter sensitivity analysis, it is necessary to sample the variables within their range. Latin Hypercube Sampling (LHS) is a type of stratified random sampling technique[11]. It is capable of effectively sampling from the distribution range of variables. LHS can ensure uniform sampling of variables under small samples. Therefore, LHS is used to sample the variables in this paper. The principle of LHS is depicted as follows:

$\boldsymbol{X}$ =[X_1, X_2,..., X_m]^T is the input variable vector, and m is the number of input variables. The range of the error of variable X_i is between the lower limit a_i and the upper limit b_i: $\delta X_i \in [a_i, b_i]$, and the distribution of the error probability is uniform. If the number of samples extracted is N, the following four steps can be used to create the sample training set. Firstly, the interval(0,1) is divided into N intervals of equal size, each of which is 1/N; Secondly, randomly generate N numbers in the interval (0,1), denoted as r_1, r_2 ,..., r_N ; Thirdly, the selected value of the error of the variable X_i in the jth interval is introduced as:

$$\delta x_i = a_i + \frac{\left(j-1+r_j\right)\left(b_i - a_i\right)}{N} \tag{10}$$

Lastly, the order of the N selected points of the variable X_i error is disordered and then combined with each other with the selected points of other variable errors to form the training set of samples needed for training.

Compared with other methods, LHS reduces the variance of sample points due to stratified sampling and avoids the repetitiveness of samples. The samples are distributed in each Section. Once the sample points are sampled from this section, they will no longer be sampled. LHS maintains the independence and randomness of the samples and greatly improves the sampling efficiency.

B. *The Principle of Random Forest*

Random Forest (RF) is a statistical learning theoretical method that can be used to deal with classification and regression problems. It was proposed by Breiman in 2001[12]. RF can directly analyze high-dimensional variables without the need to reduce the dimension of samples. At the same time, RF algorithm is stable, not susceptible to outliers and noise, and not easy to appear overfitting phenomenon during training. Therefore, the method of RF processing nonlinear regression problem is applied to the error sensitivity analysis of robot geometric parameters.

The schematic diagram of random forest model is shown in Fig. 3. RF mainly uses the idea of integrated learning, which consists of a basic unit of decision trees, each of which is independent and parallel to each other. The Bootstrap sampling technique was used for each decision tree, that is, random and put back samples were extracted from the original sample set, and then the extracted sample set was input as the training sample of the tree[12]. When the decision tree is being trained and the nodes of the tree are split, some feature dimensions of fixed size are randomly selected from the multi-feature input samples for splitting. When the training of each decision tree is completed, the training results of all decision trees are integrated to form the final training results of the entire random forest model.

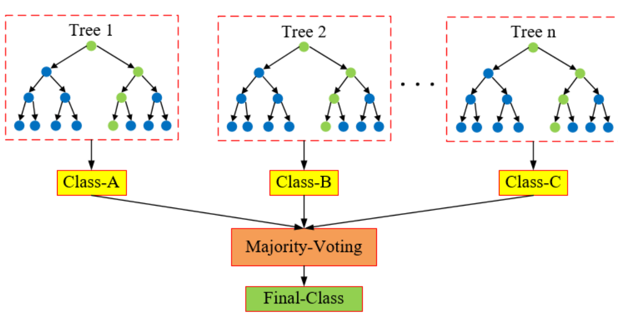

Fig. 3. Schematic diagram of RF model

Some samples in the original sample set will not participate in the construction of the decision tree, which is called OOB (Out-Of-Bag) samples of the decision tree. OOB samples can be used as sample data to test the regression effect of decision tree. If the predicted result of OOB samples is close to the regression curve fitted by decision tree, it indicates that the effect of decision tree training is better[13].

Predictor Delta Importance (PDI) may have three scenarios: positive, negative and zero[14]. The order of one of the variable values in the OOB sample is disrupted, and the order of the remaining variable values is kept unchanged, and then the OOB sample is brought back into the decision tree model for prediction, and if the prediction results instead make the error of the prediction results larger and the prediction results further away from the regression curve, i.e., the correlation between the input variables and the output response is broken, this indicates that the input variables have a greater ability to influence the output response, at which point the PDI is positive; If the predicted result is always the same after disturbing the order of the variables, the variable does not affect the output response and the PDI of this input variable is 0; If after disordering the variables, the prediction results instead have less error and the prediction results are closer to the regression curve, then the PDI is negative. The PDI size of the input variable in the whole random forest is then jointly determined by the PDI of the variable in all decision trees, and the mean value of PDI of the variable in all decision trees is used to represent the PDI size of the variable in the whole random forest.

The PDI of OOB data reflects the importance of variables to some extent and has the same characteristics as the sensitivity index in sensitivity analysis. When the PDI of an input variable is larger than that of other variables, it indicates that among all input variables, the sensitivity index of this variable is larger than that of other variables, and the influence of this variable on the output response is also higher. Otherwise, it indicates that the sensitivity of this variable is small among all input variables, and its influence on the output response is also low. Therefore, the sensitivity analysis of the robot geometric parameter error can be carried out by referring to the PDI size of random forest.

IV. Experiment and Result

In this section, the sensitivity analysis method based on RF is adopted to calculate the PDI of the geometric parameter error of the robot, and select the geometric parameter error of high sensitivity which has a great influence on the robot position error.

A. *Experiment*

First, the forward kinematics simulation program of IRB 2400 robot was written to calculate the corresponding homogeneous transformation matrix between each link, and the homogeneous transformation matrix was sequentially right multiplied to obtain the homogeneous transformation matrix from the robot base frame to the robot working frame, and then the kinematic model of the robot was established by calculating the position of the robot after its motion based on the position information before the robot works. The initial position of the robot was set with the base coordinate system, and the nominal MD-H parameters of the robot were input to obtain the robot's workspace and defined the common workspace of the robot. In this paper, the rectangular space with robot end position coordinates x, y, and z in the interval [300,1000], [-750,750], and [85,1550], respectively, was selected as the common workspace. For the IRB 2400 robot, the values of the nominal geometric parameters are shown in Table I.

TABLE I. NOMINAL GEOMETRIC PARAMETERS OF THE ROBOT

Link i	a_{i-1} / mm	d_i / mm	α_{i-1} / (°)	θ_i / (°)	Range of θ_i	β_i / (°)
1	100	615	-90	0	-180~180	-
2	705	0	0	-90	-100~110	0
3	135	0	-90	0	-60~65	-
4	0	755	90	0	-200~200	-
5	0	0	90	180	-120~120	-
6	0	85	0	0	-400~400	-

Second, based on the kinematic model of IRB 2400 robot, the robot geometric parameter error was defined, and the actual end position of the robot was obtained by inputting the actual MD-H parameters and substituting them into the robot kinematic program, and the difference between it and the ideal end location of the robot corresponding to the nominal MD-H parameters was the robot end position error, thus establishing the robot kinematic position error model.

Third, 200 sampling points were randomly chosen from the common workspace of the robot, and the 25 nominal geometric parameters corresponding to each working point were recorded. The error range of the 25 geometric parameters of the IRB 2400 robot was set, and the program of LHS method was written to generate the error data of the robot geometric parameters by substituting the error range of the geometric parameters. The error data and nominal parameters were used in the error model to determine the robot's positional errors at the sampling points.

Finally, the above error data were used as input variables, and the position errors and absolute position errors in the x, y and z directions were used as corresponding outputs to train four random forest models. When all the random forest models with 200 sampling points were trained, the mean value of PDI of 200 sampling points was taken, and the size of PDI would represent the error sensitivity of the geometric parameters of the robot, which determined the result of this random forest sensitivity analysis. Based on the results of the geometric parameter error sensitivity analysis, the error source with high sensitivity was selected.

B. Result Analysis

The geometric parameter errors and position errors of the sampling points are taken as input variables and corresponding outputs, respectively, and the training set is used to train the random forest model. After the training, the PDI of 25 geometric variable errors are shown in Table II and Fig. 4 below.

By analyzing Table II and Fig. 4, it is clear that geometric parameter errors greatly affect the end position error of IRB 2400 robot are $\delta\alpha_2$, $\delta\alpha_3$, $\delta\theta_1$, $\delta\theta_2$, and $\delta\theta_3$. $\delta\alpha_2$, $\delta\alpha_3$, $\delta\theta_1$, $\delta\theta_2$, and $\delta\theta_3$ are all angular errors. Therefore, the high sensitivity geometric parameter errors that affect the end position error of IRB 2400 robot are $\delta\alpha_2$, $\delta\alpha_3$, $\delta\theta_1$, $\delta\theta_2$, and $\delta\theta_3$, and the correction of the above five parameters should be focused on in the precise design of the robot to achieve a better accuracy compensation effect.

TABLE II. PDI OF GEOMETRIC PARAMETER ERROR

Error	δa_1	δa_2	δa_3	δa_4	δa_5	δa_6
PDI	0.0356	0.0403	0.0454	0.0419	0.0356	0.0389
δd_1	δd_2	δd_3	δd_4	δd_5	δd_6	$\delta\alpha_1$
0.0410	0.0420	0.0422	0.0308	0.0432	0.0353	0.0334
$\delta\alpha_2$	$\delta\alpha_3$	$\delta\alpha_4$	$\delta\alpha_5$	$\delta\alpha_6$	$\delta\theta_1$	$\delta\theta_2$
0.0726	0.0991	0.0036	0.0010	-0.0065	0.0789	0.1036
$\delta\theta_3$	$\delta\theta_4$	$\delta\theta_5$	$\delta\theta_6$	$\delta\beta$		
0.1015	0.0030	0.0035	-0.0067	0.0378		

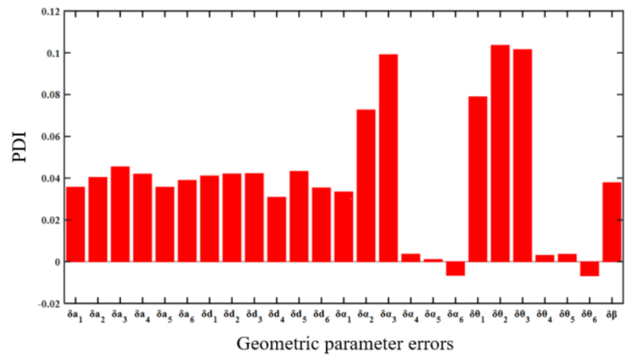

Fig. 4. Geometric parameter error sensitivity analysis results

V. VERIFICATION OF THE SENSITIVITY ANALYSIS METHOD

In order to confirm the correctness of the sensitivity analysis and whether the precision design mainly for the high sensitivity error source can improve the absolute positioning accuracy of the robot, the results of the sensitivity analysis need to be further verified. The validation procedure was mainly done by setting up a control group, one group for high sensitivity error sources and the other group for non-high sensitivity error sources, to compare the degree of improvement in the end position error of the two robots.

200 working points were randomly selected from the common working space again, and 25 nominal geometric parameters corresponding to each working point were recorded. In order to express the difference in the effect of accuracy design on different error sources, the geometric parameter errors were divided into four control groups according to the degree of influence of the geometric parameter error sources on the end position error of the robot, and the error values of several of the corresponding geometric parameters were reduced to simulate the accuracy design for high sensitivity geometric parameters. Then, using the robot's error model, the positional error for each control group's geometric parameter errors was calculated. Finally, the sensitivity analysis was verified by comparing the mean and maximum values of each group's position errors. The initial values of geometric parameter errors defined in this paper are shown in Table III.

TABLE III. THE INITIAL VALUE

Error	δa_i / (mm)	δd_i / (mm)	$\delta\alpha_i$ / (°)	$\delta\theta_i$ / (°)	$\delta\beta$ / (°)
Initial Value	0.4	0.4	0.05	0.05	0.05

Group S was set as the control reference group, and groups A, B and C were set as the experimental group. Group S does not change the initial geometric parameter error. Group A only changes the geometric parameter errors of the high sensitivity ($\delta\alpha_2$, $\delta\alpha_3$, $\delta\theta_1$, $\delta\theta_2$, and $\delta\theta_3$) by adjusting the errors to 10% of the initial errors, and the remaining geometric parameter errors remain unchanged. Group B only changes the geometric parameter errors of the non-high sensitivity (except for $\delta\alpha_2$, $\delta\alpha_3$, $\delta\theta_1$, $\delta\theta_2$, and $\delta\theta_3$) by adjusting the errors to 10% of the initial error. The remaining geometric parameter errors remain unchanged. Group C adjusts all geometric parameter errors to 10% of the initial error. By substituting the errors corresponding to the above geometric parameters into the robot kinematic error model, the mean value and maximum value of the robot terminal position errors corresponding to each group can be calculated. The test results are shown in Table IV and Fig. 5.

As can be seen from Table IV and Fig. 5, the position errors of the robots in the three experimental groups ABC are all reduced compared with those in group S. The mean position error (MPE) of group A relative to group S decreased from 2.3892mm to 1.4942mm, an increase of about 37.46%. The MPE of group B relative to group S decreased from 2.3892mm to 1.6704mm, an increase of about 30.09%. The MPE of group C relative to group S was reduced from 2.3892mm to 0.2388mm, an increase of about 90.00%. From the experimental results, it can be seen that the mean position error improvement rate(*Pa*) of group C is larger than that of groups A and B. This indicates that the accuracy design for all geometric parameter errors can reduce the position error of the robot. *Pa* of group A is higher than that of group B. Therefore, precision design for geometric parameter errors with high sensitivity can improve the positioning accuracy of the robot more effectively than that for geometric parameter errors with non-high sensitivity.

TABLE IV. ANALYSIS RESULT OF POSITION ERROR OF EACH GROUP

Group	MPE/mm	$(PE)_{max}$/mm	*Pa*
S	2.3892	4.2484	0%
A	1.4942	2.9489	37.46%
B	1.6704	2.9513	30.09%
C	0.2388	0.4247	90.00%

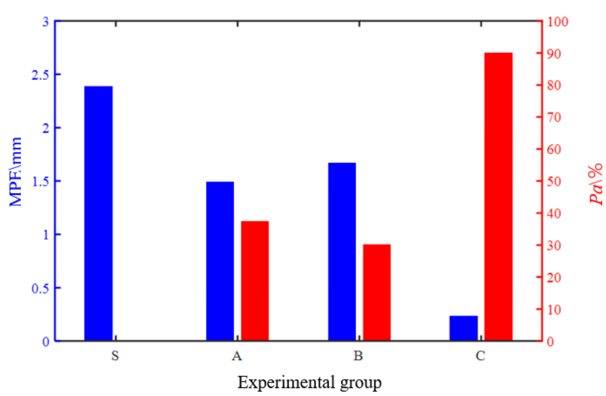

Fig. 5. Mean position error(MPE)and improvement rate(*Pa*) of each group

Although the best improvement in robot positioning accuracy was achieved in experimental group C, this group reduced all the geometric parameter errors at a cost that was too high to be realistic. In the actual accuracy design, more estimates are needed for the cost of reducing errors in geometric parameters. In order to more clearly represent the effect of cost improvement in accuracy when considering the improvement of error sources, the accuracy improvement to cost ratio (ICR) is introduced, and the ICR metric is defined as follows:

$$ICR = \frac{Pa}{Pc} \tag{11}$$

Where *Pa* refers to the reduction in the mean position error of the robot relative to the initial group (group S) as a proportion of the position error of the initial control group after each group accuracy design, and is also called the mean position error improvement rate; *Pc* refers to the ratio of the number of adjusted geometric parameter errors to the total number of geometric parameter errors. If the value of ICR is larger, it means that the group can spend less to achieve a larger improvement in positioning accuracy, and the accuracy design will be better. After the calculation of ICR for each experimental group, the results can be obtained as shown in Table V and Fig. 6.

TABLE V. THE PA, PC AND ICR VALUES OF EACH GROUP

Group	*Pa*	*Pc*	ICR
A	37.46%	20%	1.873
B	30.09%	80%	0.376
C	90.00%	100%	0.900

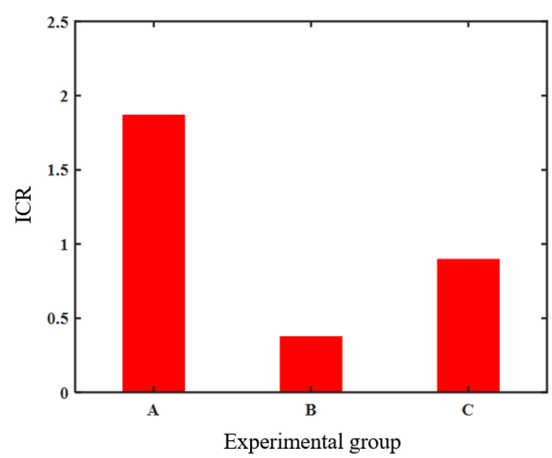

Fig. 6. The accuracy improvement to cost ratio(ICR) of each experimental group

Pa of group A relative to group S was 37.46%. The robot has a total of 25 geometric parameter errors, and group A only changes 5 of the high sensitivity geometric parameter errors ($\delta\alpha_2$, $\delta\alpha_3$, $\delta\theta_1$, $\delta\theta_2$, and $\delta\theta_3$), so the *Pc* of group A is 5/25 = 20%. *Pa* for group B relative to group S was 30.09%. Group B changed 20 non-highly sensitive geometric parameter errors, accounting for about 80% of all geometric parameter errors.

Similarly, the *Pa* of group C relative to group S is 90.00%. Group C changes all the geometric parameter errors, so the *Pc* of group C is 100%.

According to Table V and Fig. 6, the ICR of the high sensitivity geometric parameter error source for the robot end position is 1.873, while the ICR of the non-high sensitivity geometric parameter error source for the robot end position is 0.376. The ICR of all geometric parameter errors on the robot end position is 0.900. The ICR of high sensitivity geometric parameter error sources on the robot end position error is the largest.

The high sensitivity geometric parameter error ICR is about 4.98 times that of the non-high sensitivity geometric parameter error, indicating that the cost of precision design for the non-high sensitivity geometric parameter error is 4.98 times that of precision design for the high sensitivity geometric parameter error. Therefore, group A can greatly improve the positioning accuracy of the robot by reducing fewer geometric parameter errors. However, group B needs to reduce more geometric parameter errors to achieve the same effect as group A with a small reduction of errors.

The ICR of high sensitivity geometric parameter error is about 2.08 times of the ICR of all geometric parameter errors, and it is known that the cost of accuracy design for all geometric parameter errors is 2.08 times of the accuracy design for high sensitivity geometric parameter errors. Therefore, although the accuracy design for all geometric parameter errors can improve the robot positioning accuracy, it is more costly and less cost-effective. Therefore, the accuracy design of only the high sensitivity geometric parameter errors can not only improve the positioning accuracy of the robot, but also has a lower cost and high cost performance.

In summary, the RF-based sensitivity analysis method for geometric parameter errors is feasible, and the results of the sensitivity analysis are fully applicable to the accuracy design of the IRB 2400 robot. $\delta\alpha_2$, $\delta\alpha_3$, $\delta\theta_1$, $\delta\theta_2$, and $\delta\theta_3$ are highly sensitive error sources for the IRB 2400, and have a greater impact on the robot end position error than other geometric parameter error sources. Therefore, more attention needs to be paid to high-sensitivity geometric parameter error sources during accuracy design, which can substantially improve positioning accuracy at less cost. Simulation experimental results show that sensitivity analysis of geometric parameter error sources can improve the robot end positioning accuracy, which verifies the correctness and effectiveness of the method in this paper.

VI. Conclusion

In this paper, the IRB 2400 6-DOF series robot is taken as the research object, and the position error model of the robot is established on the basis of the robot kinematic model, which lays an important foundation for the subsequent sensitivity analysis. A RF-based sensitivity analysis method for geometric parameter errors of tandem robots is proposed. The sensitivity analysis of the geometric parameter errors of the robot is carried out using RF, from which the highly sensitive sources of geometric parameter errors are selected. A simulation experiment with and without precision design is conducted to verify the proposed method. The results show that, focusing on the optimization of high-sensitivity geometric parameter errors in the accuracy design of industrial robot can effectively improve the effectiveness of the accuracy design and significantly improve the positioning accuracy of the robot.

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