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Adaptive learning of vision-informed positioning and deformation error prediction for industrial robot accuracy enhancement



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Highlights:

- A vision-informed adaptive learning framework is developed for industrial robot accuracy-error prediction and maintenance.
- External vision metrology provides perception-grounded supervision for positioning-error and deformation-error modeling.
- Optimized XGBoost-based models improve nonlinear error prediction under changing configurations and loads.
- Incremental updating sustains model adaptability when new operating-condition data become available.

Abstract: Industrial robot accuracy degrades under changing configurations, workspace regions, and loading conditions, which limits its use in high-precision manufacturing. To address this issue, this paper proposes a vision-informed unified adaptive incremental learning framework for industrial robot accuracy maintenance via positioning-error and deformation-error prediction. The framework combines metaheuristic hyperparameter optimization, eXtreme Gradient Boosting (XGBoost)-based nonlinear regression, and incremental model updating to improve initial-model quality and adaptability. The method is validated on two representative tasks: positioning-error prediction using laser-tracker-based measurements and deformation-error prediction using an optical C-Track system under external loading. For the positioning-error task, evaluated under a grouped configuration–workspace protocol, incremental updating reduced the mean absolute error (MAE) from 1.080 mm to 1.003 mm and increased R^2 from 0.883 to 0.903. For the deformation-error task, Random-Walk Grey Wolf Optimizer (RWGWO)-XGBoost achieved the best overall performance among the compared methods under the same evaluation protocol, and incremental updating further reduced the mean squared error (MSE) from 0.75807 mm² to 0.41582 mm². Additional analyses of the incremental adjustment coefficient, update strategy, and computational cost further clarified the update behavior and deployment characteristics of the framework. Overall, the proposed framework provides accurate nonlinear error prediction and sustained adaptive improvement, offering practical evidence



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for vision-informed industrial robot accuracy prediction and adaptive maintenance under the tested operating conditions.

Keywords: robot learning; vision-informed robotics; industrial perception; external vision metrology; adaptive incremental learning; robot error prediction; industrial robot accuracy

1. Introduction

Industrial robots are increasingly deployed in high-precision manufacturing because of their large workspace, flexibility, cost effectiveness, and operational efficiency. They have been widely used in large-scale equipment manufacturing and precision operations such as aerospace machining, robotic milling of complex parts, industrial robotic machining, and blade polishing tasks [1–4]. However, when robots operate under changing configurations, workspace regions, and task conditions, the end-effector accuracy may degrade significantly, which restricts their broader use in applications requiring reliable high-precision performance [5,6]. In the context of intelligent vision-driven robotics, this challenge is increasingly addressed by coupling robot learning with perception systems that can observe end-effector behavior and provide feedback for adaptive modeling and accuracy maintenance.

Robot accuracy degradation is not caused by a single factor. Among the various error sources, positioning error and deformation error are two representative types. Positioning error is mainly related to configuration variation, workspace dependence, and combined geometric/non-geometric effects, whereas deformation error is more closely associated with external loading, structural compliance, and load-dependent nonlinear coupling [7–10]. Although these two error types arise from different physical mechanisms, both directly affect the final motion accuracy of the robot end-effector and therefore require effective modeling, perception-grounded measurement, and continuous updating in practical industrial environments.

For positioning-error reduction, existing studies have developed both model-based and data-driven methods. In model-based research, Nguyen *et al.* improved robot accuracy by combining an extended Kalman filter with an artificial neural network [7], Nubiola and Bonev carried out absolute calibration of an Asea Brown Boveri (ABB) industrial robot using a laser tracker [8], Chen *et al.* established the relationship between end-position error and model-parameter error for industrial robot calibration [11], Tian *et al.* proposed a repeatability prediction method for a six-degree-of-freedom (DOF) hybrid robot based on an equivalent error model [12], and Ma *et al.* modeled high-order joint-dependent kinematic errors for industrial robots [13]. Earlier sensing-assisted estimation methods were also studied by Alici and Shirinzadeh using laser-interferometry-based error estimation [14]. To better capture non-geometric effects, researchers increasingly adopted black-box learning strategies. Jin *et al.* developed a deep-learning-based error prediction model for a large optical mirror processing robot [15], Wang *et al.* proposed a deep-belief-network-based industrial robot compensation method [16], Tan *et al.* studied prediction and compensation of robot tracking error considering pose-dependent load decomposition [17], and Li *et al.* used a neural network to compensate for positioning error through iterative prediction [18]. In addition, compensation-oriented studies such as Co-Kriging-based drilling robot compensation [19], real-time compensation for a 5-DOF hybrid robot [20], incremental

extreme-learning-based compensation [21], and wireless-force-sensing-assisted robotic milling accuracy enhancement [22] further advanced this line of research. Nevertheless, most of these methods are still built for specific scenarios and rely on static models, which limits their adaptability when robot configurations, workspace conditions, or task settings change.

For deformation-error prediction under load, current methods can also be broadly divided into physical-model-based and data-driven categories. Under heavy-load operations, non-geometric errors caused by insufficient structural rigidity, joint flexible deformation, and dynamic load coupling become a critical bottleneck for high-precision robot applications [9,10]. In physical-model-based studies, Wu *et al.* proposed a sequential identification method for joint-dependent geometric errors using a laser tracker [23], Zhang *et al.* verified efficient robot positioning compensation in wire arc hybrid manufacturing systems [24], Zerun *et al.* investigated joint position-dependent stiffness parameters and robot milling deformation [9], and Xu *et al.* proposed a hierarchical compensation framework addressing geometric and non-geometric influences [25]. In parallel, adaptive error-reduction studies such as continuous path tracking with iterative learning control [26], few-shot class-incremental learning [27], incremental reinforcement learning for robot path planning [28], high-precision robot positioning based on laser tracking [29], and robust multi-sensor positioning in extreme environments [30] further suggest the importance of learning under changing conditions. These studies show that when load magnitude, processing path, or operating scenario evolves over time, static batch-trained models are prone to performance degradation caused by data distribution drift.

Recently, gradient-boosting learning and metaheuristic optimization have shown strong potential for nonlinear prediction under heterogeneous conditions. eXtreme Gradient Boosting (XGBoost) provides an efficient boosting-based regression framework [31], while Grey Wolf Optimizer (GWO) and its random-walk variant offer effective global hyperparameter search strategies [32,33]. Their combinations have achieved promising results in a variety of nonlinear prediction problems, including fracture-toughness prediction [34], mining subsidence prediction [35], wind-power forecasting [36], blast-induced ground vibration prediction [37], compressive-strength prediction [38], hidden autonomous system (AS) link prediction [39], electroencephalogram (EEG) emotion recognition [40], and radio-frequency power-amplifier modeling [41]. A preliminary conference study by our group also showed that GWO-XGBoost incremental learning is effective for robot error prediction in a single-task setting [42]. However, a unified incremental-learning perspective for different industrial robot accuracy-error tasks is still lacking.

To address the above issues, this paper proposes a vision-informed unified adaptive incremental learning framework for industrial robot accuracy maintenance via positioning-error and deformation-error prediction. The framework combines optimized XGBoost-based nonlinear regression with incremental model updating, and uses external vision metrology to provide consistent supervision signals under changing conditions. Instead of focusing on only one specific error source, the proposed method is validated on two representative tasks, namely positioning-error prediction and deformation-error prediction. The main contributions of this work are threefold. First, a perception-grounded unified learning perspective is established for two representative robot accuracy-error tasks under changing configurations, workspace regions, and loading conditions. Second, an adaptive XGBoost-based modeling and updating

framework is developed to improve initial-model quality and sustain long-term adaptability when new data become available. Third, experiments on positioning-error and deformation-error tasks, together with supplementary analyses on update sensitivity, strategy comparison, and timing characteristics, demonstrate that the proposed framework can provide accurate nonlinear error prediction and practical adaptive-maintenance capability under changing operating conditions.

2. Methods

2.1. Overall framework

To address the problem that robot accuracy errors exhibit distribution drift under changing operating conditions, this paper develops a vision-informed unified adaptive incremental learning framework based on random-walk Grey Wolf Optimizer (RWGWO)-XGBoost. The overall architecture of the proposed framework is illustrated in Figure 1. The proposed framework consists of three main modules: RWGWO-based hyperparameter optimization, XGBoost-based initial model construction, and incremental learning-based model updating. The overall workflow can be summarized as follows. First, historical data are used to construct an initial robot error prediction model. Second, the random walk RWGWO is employed to optimize the key hyperparameters of XGBoost so as to obtain a better initial model configuration. Third, when new error samples become available under new configurations, workspaces, or loading conditions, the model is updated through an incremental learning mechanism rather than full retraining.

Compared with static models trained under fixed operating conditions, the proposed framework can continuously absorb newly observed information while preserving previously learned knowledge, thereby improving the adaptability of the prediction model to changing industrial scenarios. In this study, “vision-informed” specifically means that external vision metrology (laser tracker and optical tracking) provides high-accuracy error observations for model supervision and incremental updating, while the predictor itself learns from robot-state and load-related features. It should be noted that this section only presents the unified methodological framework, whereas the task-specific definitions, data configurations, and label constructions for the positioning-error and deformation-error tasks will be introduced in Section 3.

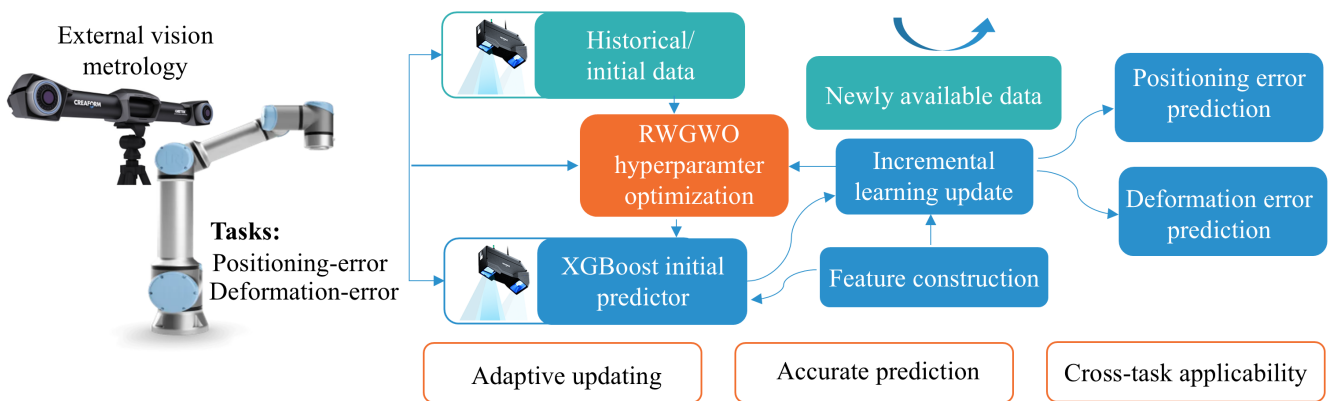


Figure 1. Vision-informed unified adaptive incremental learning framework.

2.2. XGBoost base predictor

XGBoost is adopted as the core predictor to establish the nonlinear mapping between the input features and the target robot error. As an ensemble learning algorithm based on gradient boosting, XGBoost constructs the prediction model by combining multiple regression trees. For an input sample $\mathbf{x}_i$, the predicted output can be expressed as

$$\hat{y}_i = \sum_{k=1}^K f_k(\mathbf{x}_i), \quad f_k \in \mathcal{F}, \quad (1)$$

where $\hat{y}_i$ is the prediction of the i th sample, $f_k(\cdot)$ denotes the k th regression tree, K is the total number of trees, and $\mathcal{F}$ denotes the function space of regression trees.

The objective function of XGBoost is composed of a loss term and a regularization term:

$$\text{Obj} = \sum_{i=1}^N L(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(f_k), \quad (2)$$

where y_i is the ground-truth value, $L(\cdot)$ is the loss function, and $\Omega(\cdot)$ is the regularization term used to constrain model complexity. In this work, the regularization term is written as

$$\Omega(f) = \gamma T + \frac{1}{2} \lambda \sum_{j=1}^T w_j^2, \quad (3)$$

where γ is the pruning coefficient, λ is the L_2 regularization coefficient, T is the number of leaf nodes, and w_j is the weight of the j th leaf node.

At the t th boosting iteration, the prediction is updated as

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + f_t(\mathbf{x}_i), \quad (4)$$

and the corresponding objective function becomes

$$\text{Obj}^{(t)} = \sum_{i=1}^N L(y_i, \hat{y}_i^{(t-1)} + f_t(\mathbf{x}_i)) + \Omega(f_t). \quad (5)$$

Using the second-order Taylor expansion, Equation (5) can be approximated as

$$\text{Obj}^{(t)} \approx \sum_{i=1}^N \left[g_i f_t(\mathbf{x}_i) + \frac{1}{2} h_i f_t^2(\mathbf{x}_i) \right] + \Omega(f_t), \quad (6)$$

where

$$g_i = \partial_{\hat{y}^{(t-1)}} L(y_i, \hat{y}_i^{(t-1)}), \quad h_i = \partial_{\hat{y}^{(t-1)}}^2 L(y_i, \hat{y}_i^{(t-1)}) \quad (7)$$

are the first-order and second-order derivatives of the loss function with respect to the current prediction, respectively.

Let I_j denote the set of samples assigned to the j th leaf node. Then,

$$G_j = \sum_{i \in I_j} g_i, \quad H_j = \sum_{i \in I_j} h_i. \quad (8)$$

Accordingly, the objective function can be rewritten as

$$\text{Obj}^{(t)} = \sum_{j=1}^T \left[G_j w_j + \frac{1}{2} (H_j + \lambda) w_j^2 \right] + \gamma T. \quad (9)$$

By minimizing Equation (9), the optimal weight of the j th leaf node is obtained as

$$w_j^* = -\frac{G_j}{H_j + \lambda}. \quad (10)$$

Substituting Equation (10) into Equation (9), the optimal objective value of the tree structure can be expressed as

$$\text{Obj}^{(t)*} = -\frac{1}{2} \sum_{j=1}^T \frac{G_j^2}{H_j + \lambda} + \gamma T. \quad (11)$$

Owing to the explicit regularization mechanism and second-order optimization strategy, XGBoost is well suited for industrial robot error prediction problems characterized by medium-scale data, strong nonlinearity, and coupled feature interactions.

2.3. RWGWO-based hyperparameter optimization

The predictive performance of XGBoost strongly depends on its hyperparameter configuration. To improve the quality of the initial model, this paper employs the RWGWO to globally optimize the key hyperparameters of XGBoost.

Let $\mathbf{Q}(t)$ denote the current position vector of a grey wolf and $\mathbf{Q}_p(t)$ denote the prey position vector. The distance between the grey wolf and the prey is defined as

$$\mathbf{D} = |\mathbf{C} \cdot \mathbf{Q}_p(t) - \mathbf{Q}(t)|, \quad (12)$$

and the position update rule is written as

$$\mathbf{Q}(t+1) = \mathbf{Q}_p(t) - \mathbf{A} \cdot \mathbf{D}, \quad (13)$$

where

$$\mathbf{A} = 2\mathbf{a} \cdot \mathbf{r}_1 - \mathbf{a}, \quad (14)$$

$$\mathbf{C} = 2\mathbf{r}_2, \quad (15)$$

and

$$\mathbf{a} = 2 - 2 \frac{t}{t_{\max}}. \quad (16)$$

Here, $\mathbf{r}_1$ and $\mathbf{r}_2$ are random vectors in $[0, 1]$, t is the current iteration number, and $t_{\max}$ is the maximum number of iterations.

In the standard Grey Wolf Optimizer (GWO), the three best individuals, namely the α -, β -, and δ -wolves, guide the position update of the remaining wolves. Their distances to the current wolf are computed as

$$\mathbf{D}_\alpha = |\mathbf{C}_1 \mathbf{Q}_\alpha - \mathbf{Q}|, \quad \mathbf{D}_\beta = |\mathbf{C}_2 \mathbf{Q}_\beta - \mathbf{Q}|, \quad \mathbf{D}_\delta = |\mathbf{C}_3 \mathbf{Q}_\delta - \mathbf{Q}|, \quad (17)$$

and the corresponding candidate positions are

$$\mathbf{Q}_1 = \mathbf{Q}_\alpha - \mathbf{A}_1 \mathbf{D}_\alpha, \quad \mathbf{Q}_2 = \mathbf{Q}_\beta - \mathbf{A}_2 \mathbf{D}_\beta, \quad \mathbf{Q}_3 = \mathbf{Q}_\delta - \mathbf{A}_3 \mathbf{D}_\delta. \quad (18)$$

The final updated position is obtained by

$$\mathbf{Q}(t+1) = \frac{\mathbf{Q}_1 + \mathbf{Q}_2 + \mathbf{Q}_3}{3}. \quad (19)$$

To enhance the exploration capability and reduce the risk of premature convergence, RWGWO introduces a random walk perturbation around the best solutions. The random walk process can be written as

$$W^N = W^{N-1} + s^N, \quad (20)$$

where W^N and W^{N-1} denote the random walk states at the N th and $(N-1)$ th steps, respectively, and s^N is the random step size generated from a random distribution.

In this study, the position vector of each grey wolf corresponds to a candidate hyperparameter combination of XGBoost. The optimized hyperparameters mainly include `gamma`, `learning_rate`, and `n_estimators`. The fitness value is defined by the mean squared error (MSE) on the validation set. Through iterative optimization, RWGWO outputs the optimal hyperparameter combination for constructing the initial prediction model.

2.4. Initial model construction

After obtaining the optimal hyperparameters from RWGWO, they are fed into XGBoost to construct the initial error prediction model. The construction process can be summarized as follows. First, the search ranges of the key hyperparameters are determined based on prior knowledge, and the population size and maximum iteration number of RWGWO are initialized. Second, each candidate hyperparameter combination is mapped to an XGBoost model and evaluated using the validation-set MSE. Third, the best three solutions are retained and updated through the RWGWO search process. Finally, when the stopping criterion is satisfied, the best hyperparameter combination is used to train the initial RWGWO-XGBoost model.

Compared with directly using empirically selected parameters, the RWGWO-optimized initial model generally provides a better starting point for subsequent incremental updating in terms of both prediction accuracy and generalization ability.

2.5. Incremental learning update mechanism

In long-term industrial applications, robots inevitably experience new configurations, new workspaces, new trajectories, and new loading conditions. As a result, the data distribution observed during operation may gradually deviate from that of the initial training set. To address this issue, an incremental learning mechanism is introduced to continuously update the prediction model.

The core idea of incremental learning is to preserve the previously learned tree structure, update the leaf-node weights using newly collected data, and append new trees when necessary so as to capture newly emerged error patterns. Compared with full retraining, this strategy can significantly reduce the computational burden while retaining the knowledge accumulated from earlier training.

Let D_{basic} denote the size of the initial dataset, D_{input} the size of the newly added dataset, and T_{basic} the number of trees in the initial model. Then, the number of newly added trees in the incremental stage

is determined as

$$T_{\text{incre}} = \frac{D_{\text{input}}}{D_{\text{basic}}} \times T_{\text{basic}} \times \rho, \quad (21)$$

where ρ is an incremental adjustment coefficient used to control the update strength. When the newly collected data are limited or the operating-condition change is mild, a conservative update can be adopted. In contrast, when the new data introduce more significant distribution drift, a larger ρ can be used to improve the model adaptability. In practice, the value of ρ should be selected by considering the trade-off between update conservativeness and adaptation strength, and a sensitivity analysis is provided in Section 3.4 to further illustrate its practical influence under the deformation-error setting.

Through the above incremental updating mechanism, the proposed framework can continuously adapt to changing operating conditions while preserving useful historical knowledge, thereby improving the long-term applicability and engineering practicality of robot error prediction models.

3. Results

3.1. Experimental platform

The experimental platform used in this study is shown in Figure 2. It includes a collaborative robot, a C-Track stereo tracking system, a 6-axis force/torque sensor, optical targets, and a measuring probe. The platform provides robot state, end-effector pose, and load-related measurements for positioning-error and deformation-error prediction.

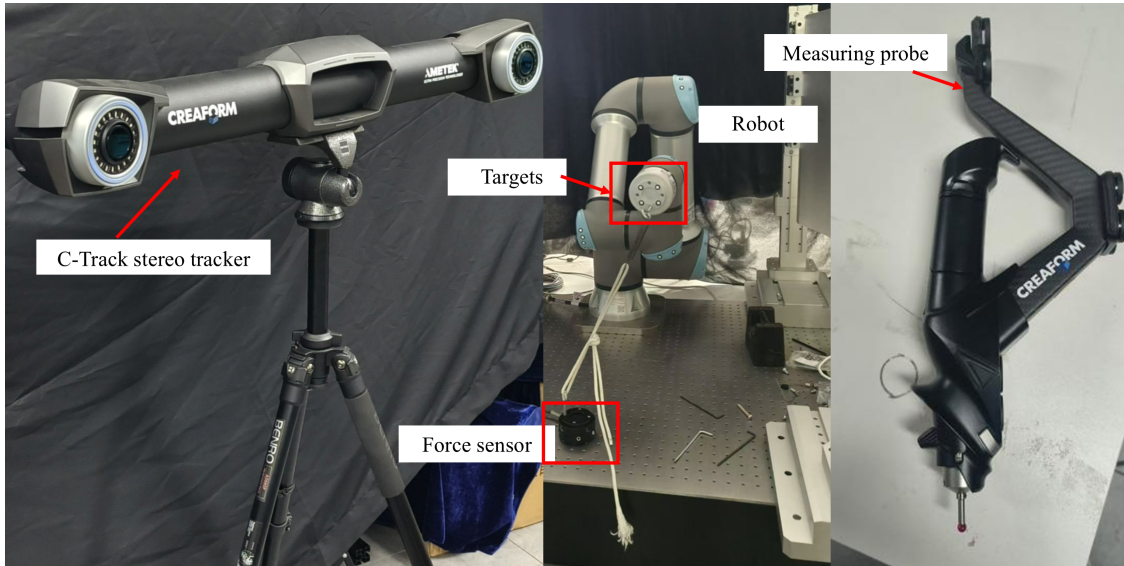


Figure 2. Experimental platform for positioning-error and deformation-error data acquisition.

3.2. Experimental setup and evaluation protocol

Experiments were conducted on two tasks: positioning-error prediction and deformation-error prediction.

For the positioning-error task, a Universal industrial robot and an external laser-tracker-based vision measurement system were used. A total of 4000 samples were collected to cover representative robot configurations and workspace regions. The input consisted of six joint angles, and the output was the multi-output positioning error of the robot end-effector. The dataset followed a grouped

configuration–workspace protocol, with grouped training data used for initial model construction and incremental updating, and a held-out grouped test set used for final evaluation.

For the deformation-error task, experiments were performed on a UR16e robot equipped with a Robotiq FT300 force sensor and a Creaform C-Track optical measurement system. Latin hypercube sampling was adopted within the workspace, with $x \in [-650, -400]$ mm, $y \in [-400, 150]$ mm, and $z \in [200, 500]$ mm. A total of 400 samples were collected. Each sample contained 12 input features, including 6 joint angles, 3 theoretical position variables, and 3 force-related variables, while the output was the 3D deformation error of the end-effector. The dataset was divided into 320 training samples and 80 test samples. For incremental learning evaluation, 160 samples were used for initial training, and the remaining 160 samples were sequentially introduced over four update rounds.

Model performance was evaluated using mean absolute error (MAE), mean squared error (MSE), mean squared logarithmic error (MSLE), and R^2 , where N is the number of test samples, y_i is the measured value, and $\hat{y}_i$ is the predicted value.

3.3. Results on the positioning-error task

For the positioning-error task, the proposed framework was evaluated using the 4000-sample dataset collected on the Universal robot platform. The six joint angles were used as the input, and the multi-output positioning error of the robot end-effector was taken as the predictive target. The performance was assessed under the grouped configuration–workspace protocol defined in Section 3.2, where evaluation groups were separated from the training groups to test generalization under changing operating conditions.

3.3.1. Prediction performance and incremental learning results

After RWGWO-based hyperparameter optimization, the positioning-error model was evaluated on the held-out grouped test set. The grouped evaluation results before and after incremental updating are summarized in Table 1. The optimized initial model achieved an MAE of 1.080 mm, an MSE of 2.689 mm², and an R^2 of 0.883 on the grouped test set. After incremental updating with newly introduced groups, the MAE was further reduced to 1.003 mm and the MSE to 2.231 mm², while the R^2 increased to 0.903.

Table 1. Grouped evaluation results of the positioning-error model before and after incremental updating.

Model stage	MAE (mm)	MSE (mm ²)	R^2
Optimized initial model	1.080	2.689	0.883
Incrementally updated model	1.003	2.231	0.903

To further provide a sample-level illustration of the gain brought by incremental updating, Figure 3 shows the residual change on the held-out grouped test set after updating. Here, a negative value indicates that the incrementally updated model yields a smaller residual norm than the optimized initial model. It can be seen that 511 out of 899 test samples showed improved residuals after updating, accounting for 56.8% of the grouped test set, and the mean residual change was -0.288 . These results indicate that the proposed framework can not only maintain effective grouped generalization on the positioning-error task, but also obtain a further practical gain when new data are introduced for model updating.

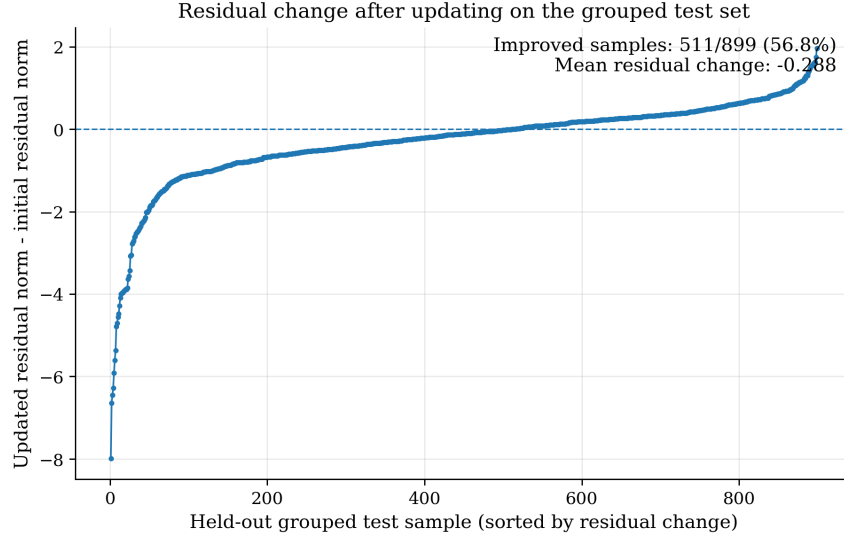


Figure 3. Residual change after incremental updating on the held-out grouped test set for the positioning-error task. Negative values indicate that the incrementally updated model yields a smaller residual norm than the optimized initial model.

3.3.2. Discussion of positioning-error results

The above results demonstrate two main points on the positioning-error task. First, the grouped configuration–workspace evaluation shows that the proposed framework generalizes across held-out groups that are separated from the training data at the group level. Second, incremental updating still improved the grouped test performance, reducing the MAE from 1.080 mm to 1.003 mm and the MSE from 2.689 mm² to 2.231 mm². This indicates that the proposed framework can preserve useful prior knowledge while adapting to newly introduced positioning-error patterns under changing operating conditions.

3.4. Results on the deformation-error task

For the deformation-error task, experiments were conducted on the UR16e platform under external loading conditions. Each sample contained 12 input features, including 6 joint-angle variables, 3 theoretical position variables, and 3 force-related variables, while the output corresponded to the 3D deformation error of the end-effector. In this task, the proposed framework was evaluated from multiple aspects, including model comparison, incremental learning performance, update sensitivity, alternative update-strategy comparison, computational cost analysis, and ablation analysis.

3.4.1. Model comparison and representative prediction results

To evaluate the prediction capability of the proposed framework, GWO-XGBoost, RWGWO-XGBoost, multilayer perceptron (MLP), random forest (RF), and support vector regression (SVR) were compared on the same deformation-error dataset using the same data split and evaluation metrics. The quantitative results are listed in Table 2. Overall, RWGWO-XGBoost achieved the best overall performance among the compared methods, while GWO-XGBoost remained competitive relative to the conventional regression baselines under the same evaluation protocol. The direct comparison between RWGWO-XGBoost and GWO-XGBoost further shows that the random-walk-enhanced strategy provided a better overall search result in the present setting.

Table 2. Performance comparison between optimized XGBoost-based models and conventional regression baselines on the deformation-error task under the same evaluation protocol.

Name	MSE	MAE	MSLE	R^2	Time/s
RWGWO-XGBoost	0.55568	0.36561	0.05148	0.59319	1.234
GWO-XGBoost	0.57688	0.47139	0.05890	0.45508	1.104
MLP	1.05313	0.72026	0.12499	-0.20698	0.424
RF	0.89142	0.40385	0.06312	-1.33826	0.469
SVR	1.22038	0.51140	0.05295	0.38687	0.229

These results suggest that the optimized XGBoost-based framework effectively captures the nonlinear coupling among joint configuration, theoretical position, and force-related inputs, while the random-walk perturbation further improves performance under the present setting.

Representative prediction residuals in the three Cartesian directions are illustrated in Figure 4. The axis-wise mean absolute errors were 0.343 mm in the x -direction, 0.652 mm in the y -direction, and 0.101 mm in the z -direction. It can be observed that the z -direction prediction residual was the most stable, whereas the y -direction showed relatively larger fluctuation and several prominent outliers. This directional discrepancy is mainly related to the inconsistency of robot compliance across different directions under external loading. It is also influenced by the unequal excitation distribution of different directional components in the sampled workspace and the different sensitivities of axis-wise deformation responses to the input features. Even so, the residuals in most samples remained clustered around zero, indicating that the proposed model maintained acceptable prediction consistency across the three directions.

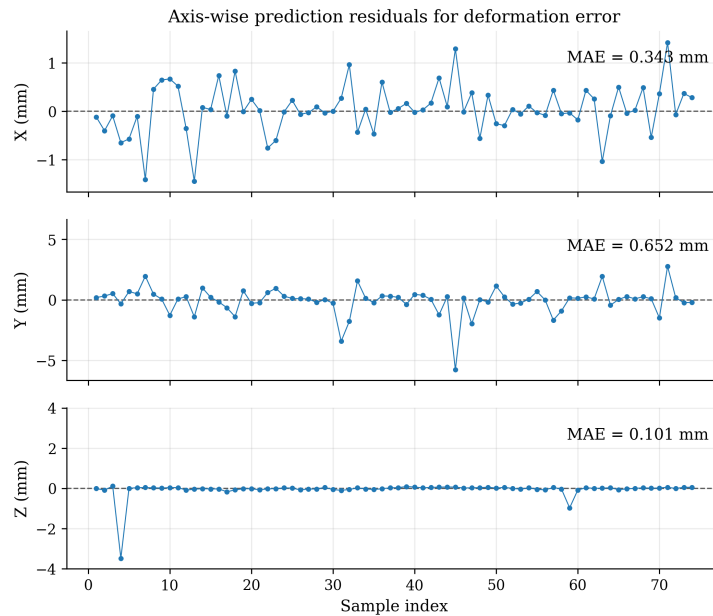


Figure 4. Axis-wise prediction residuals of RWGWO-XGBoost on the deformation-error task.

3.4.2. Incremental learning results

To evaluate the adaptability of the proposed framework to newly encountered scenarios, incremental learning experiments were conducted by progressively introducing newly collected data after the initial

model was established. Specifically, the model was first initialized using the 160-sample initial training set, and the remaining 160 samples were then sequentially introduced over four update rounds. The main quantitative results are summarized in Table 3.

The results reveal a clear improvement during the early stage of incremental updating. In the first two rounds, the MSE decreased from 0.75807 to 0.47389 and the MAE dropped from 0.58748 to 0.37425, showing that the model could rapidly adapt to the newly introduced data. From the third round onward, the improvement became smaller, with the MSE gradually approaching 0.41582. This suggests that the model had already captured most of the new deformation-error patterns and was moving toward convergence.

To further provide a sample-level illustration of the gain brought by incremental updating, Figure 5 compares the deformation error before correction and after model-updated correction under a new scenario. The mean 3D error norm decreased from 3.4122 mm to 0.8480 mm, corresponding to a mean reduction of 75.1%. At the axis level, the mean absolute error reductions were 74.5% in the x -direction, 77.5% in the y -direction, and 74.8% in the z -direction. Moreover, 66 out of 74 samples showed a smaller 3D residual after model-updated correction. These results indicate that the proposed framework can effectively transfer previously learned knowledge to new load-related scenarios and provide a clear practical gain after model updating.

Table 3. Incremental learning results of RWGWO-XGBoost on the deformation-error task.

Run	MSE	MAE	MSLE	R^2
1	0.75807	0.58748	0.07938	0.45183
2	0.47389	0.37425	0.05699	0.55862
3	0.43069	0.33961	0.05226	0.57294
4	0.41452	0.33368	0.05250	0.61824
5	0.41582	0.34610	0.06435	0.61581

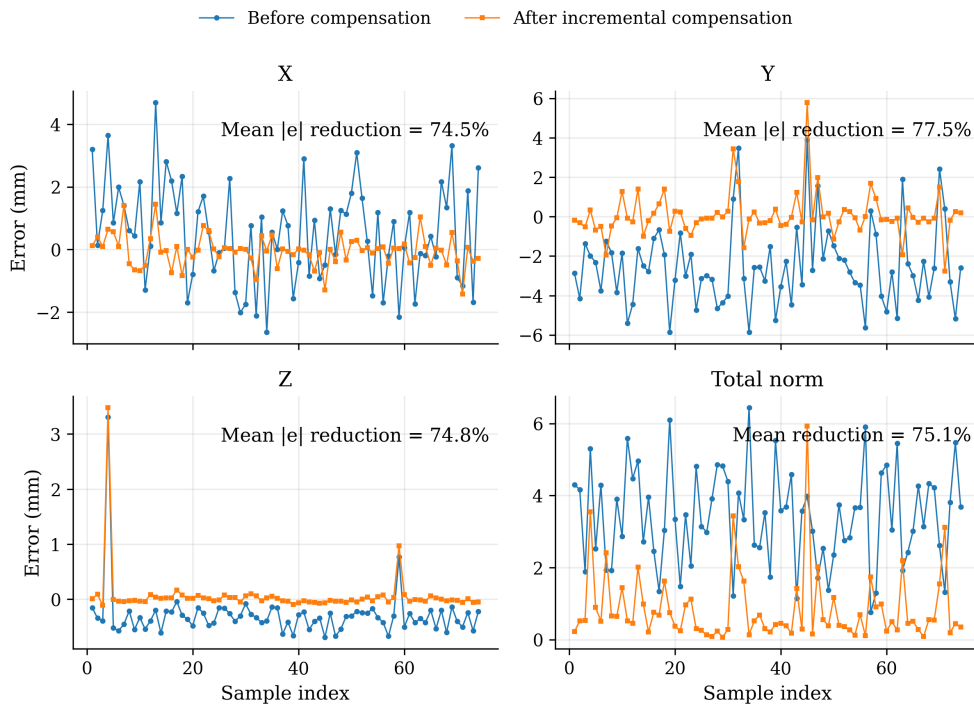


Figure 5. Representative deformation-error comparison before correction and after model-updated correction under a new scenario.

3.4.3. Sensitivity analysis of the incremental adjustment coefficient

To further clarify the role of the incremental adjustment coefficient ρ in Equation (21), a sensitivity analysis was conducted on the deformation-error task under the incremental evaluation setting. The value of ρ controls the update strength by determining the number of newly added trees at each incremental stage. When ρ is too small, the update becomes overly conservative and the adaptation to newly introduced data may be insufficient. In contrast, an excessively large ρ may lead to overly aggressive updating and slightly reduced stability.

The quantitative results are summarized in Table 4. As ρ increases from 0.25 to 1.00, both MSE and MAE gradually decrease, indicating that a moderate increase in update strength helps the model absorb newly introduced deformation-error patterns more effectively. When ρ is further increased beyond 1.00, the performance improvement becomes marginal and slight fluctuation can be observed. In particular, the results around $\rho = 1.00$ and $\rho = 1.25$ remain close, suggesting that the model performance has already approached a relatively stable range. Considering both error level and update stability, $\rho = 1.0$ was adopted as the default setting in this study.

Table 4. Sensitivity analysis of the incremental adjustment coefficient ρ on the deformation-error task.

ρ	Added trees per update	MSE (mm ²)	MAE (mm)	R^2
0.25	2	0.49231	0.40182	0.54127
0.50	5	0.45168	0.37254	0.58394
0.75	8	0.42847	0.35211	0.60736
1.00	10	0.41582	0.34610	0.61581
1.25	12	0.42096	0.34873	0.61344
1.50	15	0.43458	0.35692	0.60618

3.4.4. Comparison with alternative update strategies

To further examine the practical value of the proposed incremental update mechanism, two representative alternative update strategies were introduced for comparison, namely full retraining on the accumulated old and new data, and retraining on newly introduced data only. This comparison was conducted under the same incremental evaluation setting to examine how different update strategies affect prediction accuracy and update efficiency.

The comparison results are summarized in Table 5. Full retraining achieved the lowest MSE and MAE among the compared strategies, and can therefore be regarded as an upper-bound reference in terms of numerical accuracy. However, the proposed incremental update still outperformed retraining on newly introduced data only, indicating that preserving previously learned knowledge is beneficial for maintaining model stability when new scenarios are introduced. At the same time, the cumulative update time of the proposed strategy remained slightly lower than that of full retraining. These results suggest that the main value of the proposed strategy lies in providing a more balanced trade-off between knowledge retention, predictive performance, and update efficiency, rather than replacing full retraining as the absolute best-case solution in terms of numerical accuracy.

Table 5. Comparison of different update strategies on the deformation-error task under the same incremental evaluation setting.

Method	Cumulative Time/s	MSE (mm ²)	MAE (mm)	R ²
Proposed incremental update	6.192	0.41582	0.34610	0.61581
Full retraining (old+new data)	7.486	0.39864	0.33927	0.63142
Retraining on new data only	4.824	0.48735	0.38984	0.57426

3.4.5. Computational cost analysis

To analyze the practical deployment characteristics of the proposed framework, the computational cost of three core stages was further measured, including initial model training, single-sample online inference, and incremental model updating. The corresponding results are summarized in Table 6.

The initial model training required 1.490 s under the present deformation-error setting. For online deployment, the average single-sample inference latency was 1.393 ms, with a P95 latency of 2.250 ms, indicating that the prediction stage directly related to real-time control has a lightweight computational cost. In addition, the incremental update required 1.548 s per round, with a cumulative cost of 6.192 s over four update rounds. These results suggest that initial training and incremental updating are more suitable for offline or intermittent execution, whereas the online inference stage is sufficiently lightweight for practical deployment.

Table 6. Three-stage computational cost analysis on the deformation-error task.

Stage	Time/s	Average latency/ms	P95 latency/ms
Initial model training	1.490	N/A	N/A
Single-sample inference	N/A	1.393	2.250
Incremental update (per round)	1.548	N/A	N/A
Incremental update (4 rounds cumulative)	6.192	N/A	N/A

3.4.6. Ablation study

To further examine the respective contributions of hyperparameter optimization, the XGBoost backbone, and incremental learning, an ablation study was conducted. The comparison results are given in Table 7, and the corresponding visualization is presented in Figure 6.

Table 7. Performance comparison of different variants in the ablation study for the deformation-error task.

Name	MSE	MAE	MSLE	R ²
Basic_op	2.6183	1.6418	0.2274	0.43651
All_op	0.5557	0.3656	0.0514	0.59319
Basic_no_op	2.7382	1.6813	0.2616	0.41871
All_no_op	0.5718	0.3961	0.0598	0.58394
Incre_begin_no_op	2.5157	1.7279	0.2416	0.42157
Incre_end_no_op	0.4891	0.3677	0.0653	0.60614
RWGWO-incre_begin	0.7580	0.5875	0.0793	0.45183
RWGWO-incre_end	0.4158	0.3461	0.0644	0.61581

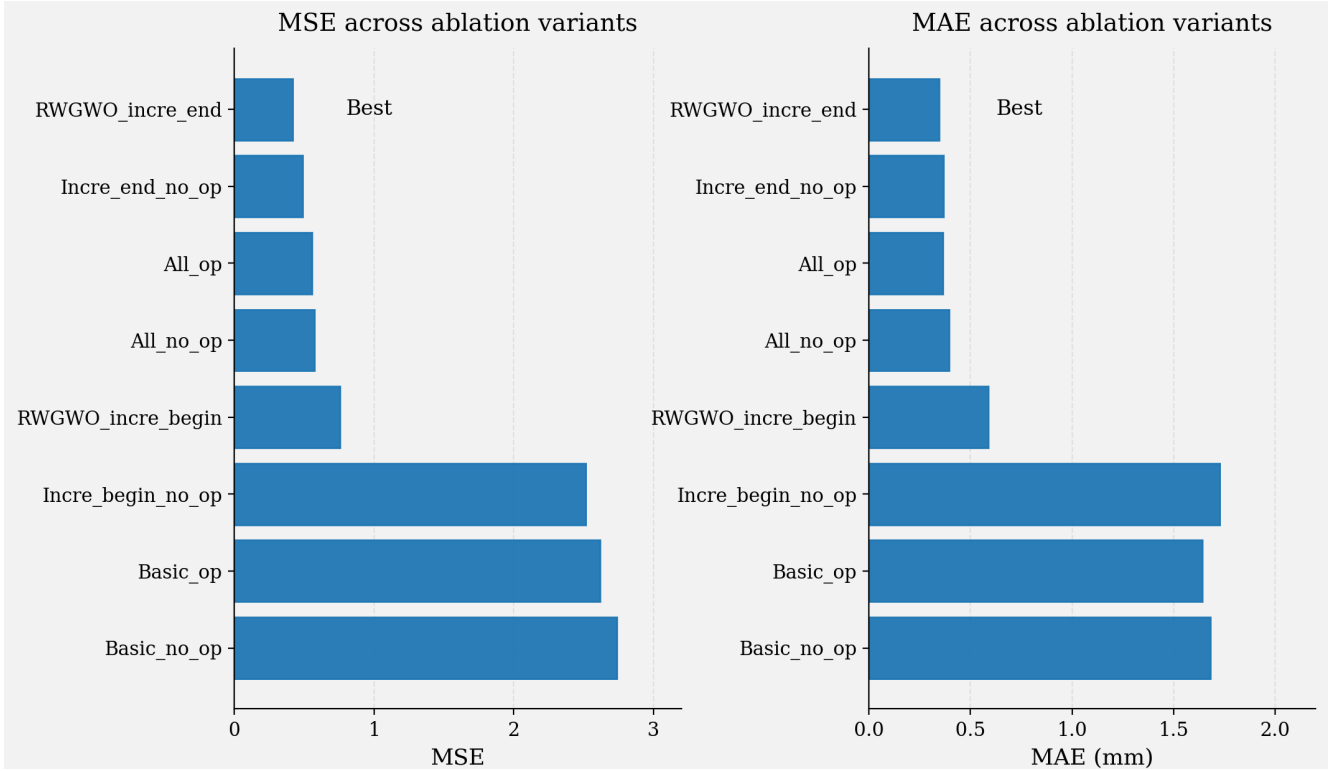


Figure 6. Visualization of the ablation-study results on the deformation-error task.

Several findings are evident. First, the final optimized incremental model, RWGWO-incre_end, achieved the best overall performance, with the lowest MSE of 0.4158 and the lowest MAE of 0.3461. Second, the comparison between RWGWO-incre_begin and RWGWO-incre_end shows that incremental updating substantially improved the model once new data were introduced. Third, the comparison between Incre_end_no_op and RWGWO-incre_end indicates that hyperparameter optimization still contributed to the final gain, although the gap became smaller after sufficient updating. Overall, the ablation results show that both incremental updating and RWGWO-based hyperparameter optimization contribute to the final performance improvement of the proposed framework.

Overall, the deformation-error experiments demonstrate that RWGWO-XGBoost achieved the best overall predictive performance among the compared methods, while the proposed incremental update mechanism maintained strong adaptability when new load-related data were progressively introduced.

4. Discussion

The present study shows that the proposed framework is an adaptive learning pipeline integrating optimized XGBoost-based modeling, external vision supervision, and incremental updating. XGBoost provides the nonlinear mapping capability for robot accuracy-error prediction, while metaheuristic hyperparameter optimization improves initial-model quality by identifying more suitable parameter configurations. On this basis, incremental learning enables the model to absorb newly observed data without repeated full retraining.

Another key point is that optimized initial modeling and incremental learning play complementary roles. The optimized XGBoost-based models provide a stronger starting point for subsequent prediction and updating, which is especially important when the initial training data are limited or unevenly distributed. In

contrast, incremental learning mainly addresses the performance degradation caused by changing operating conditions. Its value was particularly evident in the deformation-error task, where the model progressively reduced the MSE from 0.7581 to 0.4158 as new data were introduced. This suggests that initial-model quality and continual adaptation are both necessary for maintaining stable prediction performance in practice.

The results also explain why static offline models are often insufficient for long-term industrial use. In robot accuracy-error prediction, the data distribution is inherently condition-dependent. Once the robot enters new workspace regions, adopts new configurations, or experiences new loading conditions, the original training set may no longer adequately represent the current scenario. In such cases, a model trained only once may gradually lose accuracy. The proposed incremental strategy provides a practical alternative by updating the model according to newly collected samples, thereby reducing the need for repeated full-scale recalibration.

From an engineering perspective, the framework is attractive because it provides a unified implementation route for different robot accuracy-error problems while keeping the modeling process data-driven and computationally manageable. The positioning-error results show that the framework can support large-scale workspace-dependent accuracy modeling, whereas the deformation-error results show that it can also capture more complex load-related error behavior. This suggests that the framework can serve as a reusable prediction module for robot accuracy maintenance when different error sources need to be handled under a consistent learning strategy.

Several limitations should also be acknowledged. First, the two tasks were validated on different datasets and under different experimental settings, so the present study demonstrates methodological generality rather than a single physically unified total-error model. Second, the current work focuses on error prediction and adaptive updating, while the final closed-loop compensation effect on actual task execution was not systematically evaluated in one integrated experiment. Third, although external vision systems were used to generate supervision signals, the predictor did not yet directly consume image-level or point-cloud-level perception features. Fourth, the deformation-error dataset was smaller than the positioning-error dataset because of its higher acquisition cost, which may limit the breadth of scenario coverage. In addition, the current study did not yet include systematic validation across different robot platforms or different robot individuals. Future work should therefore investigate tighter coupling between visual perception and prediction, joint multi-error modeling, broader cross-scenario validation, and validation across more robot platforms and operating conditions.

Taken together, the current results provide evidence for adaptive error prediction and updating under the tested operating conditions, and support the practical feasibility of the proposed framework within the present validation scope.

4.1. Implications for vision-driven robotics

The experimental results show that the proposed vision-informed adaptive learning framework consistently improves robot accuracy-error prediction under changing conditions. On the positioning-error task, the optimized model achieved improved grouped-test prediction performance after incremental updating. On the deformation-error task, RWGWO-XGBoost achieved the best overall performance among the compared methods, indicating that the framework can effectively capture the nonlinear coupling

among joint states, position-related variables, and load-related variables under the tested setting. Because both tasks rely on external vision metrology for error observation, the framework serves as a perception-informed learning module for industrial robot accuracy maintenance.

Another important finding is that incremental learning plays a critical role in maintaining prediction performance when new data become available. In the positioning-error task, the optimized incremental model achieved the best overall performance after updating. In the deformation-error task, the prediction error was progressively reduced during the updating process, showing that the model could adapt to newly introduced deformation patterns. Additional analyses on the incremental adjustment coefficient, alternative update strategies, and computational cost further clarified the practical deployment characteristics of the framework. These results suggest that the proposed framework is suitable not only for initial error modeling, but also for long-term adaptive robot accuracy maintenance in changing industrial scenarios where perception measurements are continuously accumulated.

5. Conclusion

This paper proposed a vision-informed unified adaptive incremental learning framework for industrial robot accuracy-error prediction and maintenance. The framework combines optimized XGBoost-based nonlinear regression with incremental model updating, and it was validated on two representative tasks: positioning-error prediction and deformation-error prediction.

On the positioning-error task, evaluated under a grouped configuration–workspace protocol, the optimized initial model achieved an MAE of 1.080 mm, an MSE of 2.689 mm², and an R^2 of 0.883, while incremental updating further reduced the MAE to 1.003 mm and the MSE to 2.231 mm², with the R^2 increasing to 0.903. On the deformation-error task, RWGWO-XGBoost achieved the best overall performance among the compared methods under the same evaluation protocol. In particular, the direct comparison between RWGWO-XGBoost and GWO-XGBoost showed that the random-walk-enhanced strategy provided a better overall search result in the present setting, while incremental updating reduced the MSE from 0.75807 mm² to 0.41582 mm² as new data were introduced.

Additional analyses on the incremental adjustment coefficient, update strategy, and computational cost further clarified the update behavior, strategy trade-offs, and deployment characteristics of the framework. Overall, the results demonstrate that the proposed framework can provide accurate nonlinear error prediction and sustained adaptive improvement under changing operating conditions, and provide practical evidence for vision-informed industrial robot accuracy prediction and adaptive maintenance under the tested settings.

6. Future work

Future work will focus on four directions: joint multi-error modeling with unified perception representations, tighter integration of predicted errors into closed-loop perception feedback compensation and task-level control, broader validation across more robot platforms and operating conditions together with direct image/point-cloud feature integration, and more systematic analysis of the stability, convergence behavior, and related theoretical properties of the incremental updating process.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declaration of generative AI and AI-assisted technologies

During the preparation and revision of this manuscript, the authors used ChatGPT as an AI-assisted tool to support language polishing, grammar checking, readability improvement, and wording-level editing in parts of the manuscript. The AI-assisted tool was not used to generate the scientific ideas, experimental design, experimental data, data analysis, results, or conclusions. All AI-assisted edits were carefully reviewed and approved by the authors, who take full responsibility for the content of the manuscript.

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Authors' contribution

Conceptualization, Zesheng Guo and Zhaoyang Liao; methodology and software, Zesheng Guo; validation, Xubin Lin and Zhihao Xu; data curation, Xuefeng Zhou; writing—original draft preparation, Zesheng Guo; writing—review and editing, Hongmin Wu and Zhaoyang Liao; supervision, Zhaoyang Liao. All authors have read and agreed to the published version of the manuscript.

Conflicts of interest

The authors declare no conflicts of interest.

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