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Data-Driven Parameter Self-Tuning and Performance Degradation Detection of Industrial Robot Joint Servo Systems

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ABSTRACT

To address the difficulty of conventional tuning methods in adapting to time-varying degradation and the limited capability of existing degradation detection approaches to directly support control compensation, this paper proposes a data-driven degradation-aware parameter self-tuning method for industrial robot joint servo systems. First, a set of degradation-sensitive features is constructed from closed-loop operational data by incorporating error-related, response-related, and control-related characteristics, and a health indicator is further established to describe the evolution of the performance state of the joint servo system. Second, a tuning trigger mechanism is designed according to the state stratification and variation trend of the health indicator, and the key parameters in the position and speed loops are updated in a data-driven manner using a composite control performance index, so as to achieve performance recovery under degraded conditions. Finally, comparative experiments under multiple operating conditions are carried out on an industrial robot joint servo platform to validate the effectiveness of the proposed method in degradation detection, self-tuning control, and overall performance improvement. The results show that the proposed method can effectively identify servo performance degradation and adaptively adjust controller parameters under different degradation levels, thereby improving trajectory tracking capability, dynamic behavior, and operational adaptability. This study provides a useful reference for intelligent monitoring and adaptive optimal control of industrial robot joint servo systems.

KEYWORDS
industrial robot, joint servo system, performance degradation detection, parameter self-tuning, data-driven

INTRODUCTION

With the rapid development of intelligent manufacturing and flexible automation, industrial robots have been widely deployed in assembly, welding, handling, polishing, and high-precision machining tasks, where motion quality, control accuracy, and operational reliability directly affect production efficiency and product quality[1-3]. As the core unit responsible for motion execution, the joint servo system plays a crucial role in position tracking, speed regulation, and dynamic response, and its performance largely determines the overall trajectory accuracy, repeatability, and stability of the robot[4, 5]. However, under long-term operation and complex working conditions, the joint servo system is inevitably affected by friction variation, load fluctuation, transmission wear, thermal effects, and external disturbances[6]. These factors gradually alter the equivalent dynamic characteristics of the system, resulting in increased tracking error, slower response, intensified oscillation, and, ultimately, performance degradation. Since conventional controller parameters are usually tuned offline under nominal conditions, they often fail to adapt to time-varying operating environments and progressive performance deterioration. Therefore, investigating degradation-aware monitoring and parameter self-tuning for industrial robot joint servo systems is of considerable theoretical significance and practical value.

In recent years, extensive efforts have been devoted to health monitoring, fault diagnosis, and servo performance optimization for industrial robot joints[7, 8]. In the area of degradation detection, existing studies mainly rely on operational signals such as current, position, velocity, vibration, and torque to perform anomaly identification and health assessment through feature extraction, state recognition, and intelligent diagnostic methods. In parallel, a variety of controller tuning approaches, including model-based, optimization-based, and data-driven methods, have been developed to improve the tracking performance and robustness of servo systems[9]. Despite these advances, several limitations remain. First, many studies focus primarily on explicit fault diagnosis, while insufficient attention has been paid to the early-stage evolution of performance degradation and its impact on control quality. Second, a considerable number of tuning methods assume fixed plant characteristics and do not adequately account for the time-varying dynamics and degradation behavior of industrial robot joints. More importantly, degradation detection and parameter tuning are often treated as two separate problems, and an integrated closed-loop framework that connects degradation awareness, parameter adaptation, and performance recovery is still lacking, which limits the practical effectiveness of existing methods in real industrial applications[10].

To address the above issues, this paper proposes a data-driven degradation-aware framework for performance degradation detection and parameter self-tuning of industrial robot joint servo systems. First, based on closed-loop operational data, a set of degradation-sensitive features is constructed by incorporating information from position error, velocity response, and control input, and a health indicator is further established to characterize the evolving performance state of the joint servo system, thereby enabling effective degradation detection and assessment. Second, on the basis of the degradation assessment results, a degradation-aware self-tuning mechanism is developed, in which the detected degradation state serves as both the triggering condition and the adjustment basis for data-driven updating of key servo control parameters, so as to improve dynamic performance and tracking accuracy under degraded conditions. Finally, comparative experiments are carried out on an industrial robot joint servo platform to validate the effectiveness of the proposed method in degradation detection, parameter self-tuning, and performance recovery. The present study aims to provide a practical and engineering-oriented solution for intelligent maintenance and high-performance operation of industrial robot joint servo systems.

PROBLEM FORMULATION OF INDUSTRIAL ROBOT JOINT SERVO PERFORMANCE DEGRADATION

Servo System Description

Industrial robot joint servo systems are typically implemented using a multi-loop control architecture, which commonly consists of a current loop, a speed loop, and a position loop[11, 12]. In practice, the current loop is usually embedded in the servo drive, while the speed and position loops are responsible for ensuring the dynamic response and trajectory tracking performance of the joint actuator. For a single robot joint, the servo plant generally includes the servo motor, power drive unit, reduction mechanism, transmission components, and the load-side mechanical structure, and is simultaneously influenced by friction, backlash, flexibility, external disturbances, and load variations. Since industrial robots often operate under complex conditions characterized by frequent start-stop motions, variable speeds, and task switching, the joint servo system exhibits pronounced nonlinearity, time-varying behavior, and parametric uncertainty, which makes it difficult to maintain nominal control performance over long-term operation.

From a control perspective, the objective of the joint servo system is to achieve fast, smooth, and accurate tracking of a prescribed position command[13]. Let $r(k)$ denote the joint reference input and $y(k)$ the actual output; then the tracking error can be expressed as $e(k) = r(k) - y(k)$. Under ideal conditions, the closed-loop system is expected to exhibit small tracking error, short settling time, low overshoot, and strong disturbance rejection capability. However, during practical operation, as the dynamic characteristics of the joint gradually change, the matching relationship between the controller parameters and the controlled plant becomes increasingly weakened, causing the system to lose its original control quality. Accordingly, in this study, the industrial robot joint servo system is regarded as a degradation-affected time-varying closed-loop control object, whose performance state can be characterized by operational data such as error response, velocity variation, control input, and related derived features.

Degradation Mechanism and Its Impact on Control Performance

Performance degradation in industrial robot joint servo systems is usually not caused directly by abrupt faults; rather, it is more commonly manifested as a gradual deterioration of dynamic performance accumulated over long-term operation and under complex working conditions[14]. Mechanistically, such degradation mainly arises from the following aspects. First, the friction characteristics may change due to lubrication variation, surface wear, and thermal effects, resulting in low-speed creeping, tracking lag, and increased steady-state error. Second, long-term wear of reducers, bearings, and transmission chains may lead to enlarged backlash, reduced stiffness, and increased transmission error, thereby weakening the consistency and accuracy of the system response. Third, load variation and external disturbances alter the equivalent inertia and force conditions of the joint, making the controller parameters tuned under nominal conditions less suitable for the current operating environment. Fourth, the parameters of the servo drive and motor may drift slowly due to temperature, current fluctuation, and component aging, further intensifying the time-varying characteristics of the system. These factors are mutually coupled and jointly drive the closed-loop dynamics of the joint servo system away from the original design state.

The influence of such degradation on control performance is mainly reflected in several aspects. First, the tracking error tends to increase progressively with the degradation level, leading to reduced trajectory tracking accuracy and degraded repeatability. Second, the dynamic response becomes slower, the settling time becomes longer, and in some cases the system may exhibit stronger oscillations or more severe overshoot. Third, in order to maintain a given level of control performance, the control input magnitude and control input magnitude may increase substantially, resulting in higher energy consumption and actuator burden. Finally, under complex working conditions, performance degradation may also reduce the robustness of the system, making it more sensitive to model uncertainty and disturbances. It should be noted that such degradation does not necessarily evolve immediately into a clearly observable fault, but it continuously erodes servo performance and may eventually become a precursor to severe failures. Therefore, instead of focusing only on the binary question of whether a fault has occurred, this study is more concerned with the performance evolution during the degradation process and its impact on controller parameter suitability[15].

Based on the above analysis, the performance degradation of an industrial robot joint servo system is defined in this paper as a dynamic state variation process that occurs in the absence of obvious structural failure, but is induced by friction variation, transmission wear, thermal effects, load disturbances, and parameter drift, and that continuously leads to a decline in closed-loop control performance.

Research Objectives

Based on the above problem description, the objectives of this study can be summarized at two levels, namely performance degradation detection and controller parameter self-tuning, which are further integrated into a unified degradation-aware control framework. First, at the level of degradation detection, this work aims to exploit multi-source data that can be directly acquired during the closed-loop operation of industrial robot joint servo systems to construct feature representations that are sensitive to degradation while remaining relatively robust to operating condition changes. On this basis, a performance indicator or health indicator is established to characterize the evolution of the joint health state. Such an indicator should not only distinguish normal operation from degraded operation, but also reflect the variation trend of degradation severity as much as possible, thereby providing a reliable basis for subsequent parameter adaptation.

Second, at the level of parameter self-tuning, the objective is to develop a degradation-aware parameter update mechanism that enables the controller to adaptively adjust key parameters according to the current performance state, so as to mitigate the control performance deterioration caused by plant characteristic variations. Considering the practical requirements of industrial robot joint servo systems in terms of stability, real-time capability, and implementation feasibility, this work does not pursue large-scale online optimization of all controller parameters. Instead, it focuses on constrained data-driven tuning of the most performance-critical parameters, so that the system can maintain satisfactory tracking accuracy, dynamic response, and disturbance rejection capability even under degraded conditions.

Furthermore, this study seeks to establish a closed-loop research paradigm of “degradation detection–state assessment–parameter adaptation–performance recovery,” in which performance degradation detection and controller parameter tuning are no longer treated as isolated problems but are coordinated within a unified framework. To this end, three core issues need to be addressed: (1) how to extract degradation-sensitive features from closed-loop operational data that can effectively reflect the degradation state of the joint; (2) how to construct a health indicator capable of quantifying the degree of performance degradation and determining the appropriate timing for parameter updating; and (3) how to achieve data-driven self-tuning of key servo parameters while ensuring closed-loop stability and engineering feasibility. Addressing these three issues will provide both theoretical support and methodological guidance for high-performance control and intelligent maintenance of industrial robot joint servo systems under complex operating conditions and long-term service scenarios.

DATA-DRIVEN PERFORMANCE DEGRADATION DETECTION METHOD

Data Acquisition and Preprocessing

To enable effective detection of performance degradation in industrial robot joint servo systems, it is first necessary to collect multi-source data that can reflect the dynamic behavior and control state of the closed-loop system. Considering the engineering accessibility of signals in practical industrial control systems and the requirement for feasible deployment, this study mainly employs joint position command, actual position, velocity response, control input, and drive current or equivalent torque as the basic observables. Among them, the deviation between the commanded position and the actual position directly reflects trajectory tracking performance, the velocity response characterizes the dynamic evolution of the system, and the control input together with current-related information can, to some extent, represent control effort and actuator load. Compared with approaches relying on additional external sensors, these signals can be directly obtained from the internal servo system and are therefore more suitable for online monitoring and practical industrial implementation. This study was conducted in compliance with the institutional ethics policy on responsible innovation and risk assessment, and received ethical approval from North China Electric Power University. All data collected were anonymized and used solely for research purposes

However, raw operational data are often affected by measurement noise, sampling fluctuation, operating condition switching, and trajectory amplitude variation. If such data are directly used for degradation analysis, the detection results may become unstable or overly sensitive to non-degradation-related factors. Therefore, appropriate preprocessing is required before feature extraction. Specifically, multi-source signals are first synchronized in time and cleared of obvious outliers to ensure temporal consistency across channels. Then, high-frequency measurement noise is suppressed באמצעות low-pass filtering, moving average smoothing, or other signal conditioning strategies. After that, signals with different scales and units are normalized to improve the comparability of subsequent feature construction and fusion analysis. Finally, continuous operational data are segmented into windowed samples according to motion cycles or prescribed trajectory segments, so as to form analysis units suitable for degradation assessment. Through these steps, the raw operational signals are transformed into time-series datasets with improved consistency, comparability, and analytical suitability, thereby laying the foundation for the extraction of degradation-sensitive features.

It should be emphasized that one of the key challenges in performance degradation detection lies in minimizing the interference of operating condition variation on degradation judgment. Operational data collected under different speeds, loads, and trajectories may differ substantially, and direct comparison of such data distributions can easily lead to condition variation being misinterpreted as degradation. To address this issue, the present study introduces the idea of condition alignment and segment-wise comparison during preprocessing, that is, degradation assessment samples are constructed under identical or comparable task conditions, while normalization and window-based statistics are used to reduce the influence of trajectory excitation differences. In this way, the extracted features can focus more on the variation of the intrinsic dynamic performance of the joint rather than superficial fluctuations caused by external operating condition differences.

To distinguish permanent degradation from instantaneous load disturbances, the framework introduces a Multi-window Confirmation mechanism. Degradation is determined only when the HI value exceeds the threshold in 5 consecutive observation windows and shows a non-stationary trend. This time-scale filtering effectively avoids false triggering of tuning caused by heavy loading on a single trajectory.

Degradation-Sensitive Feature Extraction

After obtaining the preprocessed operational data, the next step is to extract degradation-sensitive features that can effectively characterize the performance variation of the joint servo system. Since degradation in industrial robot joints does not always manifest itself as an explicit fault, but more often as gradual changes such as slower response, larger tracking error, increased control effort, and reduced dynamic consistency, the feature design should cover the aspects of control quality, dynamic response, and actuation burden as comprehensively as possible. Based on this consideration, this study constructs a degradation-sensitive feature set from three dimensions, namely error-related features, response-related features, and control-related features.

First, in terms of error-related features, this study focuses on the position tracking error and its statistical descriptors, including mean value, root mean square, peak value, absolute integral, and error rate of change. Such features directly reflect the tracking quality of the system under a prescribed trajectory and constitute the most intuitive class of indicators for describing performance degradation. When friction characteristics vary, parameters drift, or transmission wear occurs, the error distribution often exhibits shifts, broader spread, or increased occurrence of local peaks. Therefore, error-related features are highly sensitive to early signs of degradation.

Second, in terms of response-related features, this study extracts key descriptors from the relationship between the actual velocity response and the commanded response, including response delay, velocity fluctuation intensity, consistency during acceleration and deceleration phases, and local oscillation level. These features are mainly intended to characterize changes in the dynamic quality of the system. When joint transmission stiffness decreases, friction compensation becomes mismatched, or load conditions vary, the system often exhibits slower response, larger dynamic deviation, or stronger local oscillation. Therefore, response-related features can reveal the impact of degradation on closed-loop dynamic behavior from the perspective of temporal evolution.

Third, in terms of control-related features, this study further considers features associated with control input, current, or equivalent driving torque, including mean control magnitude, fluctuation level, control energy, and high-frequency adjustment components. Compared with error-related features, control-related features place greater emphasis on the “cost” required by the system to maintain a given level of control performance. After degradation occurs, even if certain tracking indices have not yet deteriorated significantly, the control input may already exhibit trends of abnormal amplification or frequent adjustment. Therefore, incorporating control-related features can improve the detectability of early-stage degradation and enhance the interpretability of the detection results.

Since a single feature is often insufficient to comprehensively describe a complex degradation process, this study adopts a multi-feature fusion strategy to construct a degradation-sensitive feature vector. To avoid excessive dimensionality, information redundancy, and unnecessary complexity in the subsequent assessment model, the initial feature set can be further screened and compressed using correlation analysis, principal component analysis, or other dimensionality reduction strategies, so that only the most representative feature components for degradation characterization are retained. In this manner, the degradation representation capability can be preserved while improving the stability and robustness of subsequent health indicator construction. Mathematical definitions of key degradation features is shown in table 1.

Table 1. Mathematical definitions of key degradation features

Formula	Calculation method
$RMSE$	$\sqrt{\frac{1}{N}\sum_{k=1}^{N}(r(k)-y(k))^2}$
MAE	$\frac{1}{N}\sum_{k=1}^{N}\mid r(k)-y(k)\mid$
V_{fluct}	$\frac{std(v_{actual})}{mean(v_{actual})}$

Health Indicator Construction and Degradation Assessment

After extracting degradation-sensitive features, this study further constructs a health indicator to characterize the performance state evolution of the joint servo system, thereby enabling quantitative assessment of the degradation process. Compared with direct judgment based on individual features, a health indicator can compress multidimensional degradation information into a unified state representation, making it more intuitive to describe the evolution from a healthy state to a degraded state. An ideal health indicator should satisfy three basic requirements. First, it should be highly sensitive to performance degradation and exhibit a clear variation trend as degradation becomes more severe. Second, it should be reasonably robust to operating condition variation and random disturbances, so as to avoid excessive sensitivity to normal fluctuations. Third, it should possess good monotonicity and interpretability, thereby providing a clear basis for the subsequent self-tuning process.

Following the above principles, this study constructs the health indicator through a multi-feature fusion scheme. Specifically, samples collected under healthy operating conditions are first used as a baseline to establish a reference feature distribution or a healthy feature space. Then, the deviation of the current operational sample from this healthy reference in the degradation-sensitive feature space is calculated using the weighted Euclidean distance between the current feature vector and the centroid of the healthy baseline distribution in the multidimensional sensitive feature space, and is further mapped into a normalized health indicator under a unified scale. A larger value of this indicator implies a greater deviation from the healthy reference state and therefore a more pronounced level of performance degradation. To enhance the stability of the assessment result, the health indicator is further processed using sliding-window statistics and smoothing over consecutive time intervals, thereby reducing the influence of instantaneous outliers and random fluctuations on degradation judgment.

On this basis, the health indicator is further used for degradation state assessment. Since the performance degradation of industrial robot joints is usually a continuous evolution process rather than a simple normal/fault binary classification problem, the system condition in this study is divided into multiple levels, such as healthy, mildly degraded, and significantly degraded, and state determination is performed according to the variation trend and threshold intervals of the health indicator. These thresholds can be determined based on the statistical characteristics of healthy samples, empirical rules, or validation experiments. In this way, the degradation detection module is able not only to determine whether the system has deviated from the healthy state, but also to describe the degree and evolution trend of degradation. More importantly, the assessment result can serve as the triggering basis and adjustment reference for the subsequent parameter self-tuning module, thereby establishing the intrinsic link between degradation detection and parameter updating. In this sense, the health indicator in this paper functions not only as a representation of performance state, but also as a key bridge in the entire degradation-aware control framework.

DEGRADATION-AWARE PARAMETER SELF-TUNING METHOD

Self-Tuning Objective and Parameter Selection

In industrial robot joint servo systems, performance degradation is ultimately manifested as a decline in control quality. Accordingly, the core objective of parameter self-tuning is not merely to modify controller parameters, but to recover tracking accuracy, dynamic response, and operational stability under degraded conditions. From this perspective, the self-tuning problem in this paper is defined as follows: once the degradation state has been identified, the key parameters that exert the most significant influence on closed-loop control performance are adjusted in a data-driven manner, so that tracking error can be reduced, settling time can be shortened, overshoot and oscillation can be suppressed, and unnecessary control effort can be minimized, while maintaining system stability and engineering feasibility. In other words, the aim of parameter self-tuning is to re-establish the matching relationship between the controller and the currently degraded plant through bounded parameter updates, thereby alleviating performance loss caused by changes in plant characteristics.

Considering that industrial robot joint servo systems usually adopt a hierarchical closed-loop structure and that the number of online adjustable parameters should remain limited, this work does not attempt to optimize all controller parameters simultaneously. Instead, it focuses on the key parameters that are both highly influential on control performance and practically feasible for engineering implementation. Specifically, the position-loop proportional gain, the speed-loop proportional gain, and the speed-loop integral gain are selected as the primary tuning parameters, while speed feedforward or friction compensation related parameters may also be introduced as auxiliary adjustment variables when necessary. This parameter selection offers two advantages. On the one hand, these parameters are closely associated with tracking accuracy, response speed, and disturbance rejection, and therefore constitute the main tuning objects affecting servo performance. On the other hand, they have clear physical meanings and direct regulatory effects, which facilitates both control performance analysis and industrial implementation. Compared with high-dimensional joint optimization, constrained self-tuning of a few key parameters can reduce computational burden and lower the potential risk of instability caused by aggressive parameter adaptation.

To quantitatively describe the objective of parameter self-tuning, the control performance of the system is represented by a comprehensive optimization target composed of multiple performance indices, including trajectory tracking error, dynamic response quality, and control effort. Among them, the tracking error is used to characterize motion accuracy, the dynamic response quality reflects settling time, overshoot, and oscillation level, and the control effort measures the amplitude and intensity of the control action. Based on these indices, parameter updating is no longer limited to minimizing a single error measure, but is instead oriented toward coordinated multi-objective performance recovery. This design is intended to avoid the situation in which improvement in one performance aspect is achieved at the cost of deterioration in others, thereby making the self-tuning result more advantageous in practical applications.

Tuning Trigger Mechanism Based on Degradation Assessment

The effective implementation of parameter self-tuning relies on a proper triggering mechanism. If the system continuously updates parameters at all times, not only will the computational burden increase, but the stability of the controller may also be compromised by excessive adjustment. On the other hand, if tuning is activated only after severe performance deterioration has already occurred, the optimal timing for compensation may be missed. Therefore, based on the health indicator constructed in Section 3, this paper develops a degradation-aware tuning trigger mechanism, so that parameter updating can be activated in a targeted manner according to the current performance state of the system, thereby balancing update frequency and control safety.

Specifically, the health indicator is adopted as the core criterion for reflecting the current performance condition of the system, and the system state is stratified according to its magnitude and evolution trend. When the health indicator remains within the normal fluctuation range, the system is regarded as being in a healthy condition and the current controller parameters are maintained. When the health indicator continuously deviates from the healthy reference interval and reaches the threshold corresponding to mild degradation, the system is considered to have entered an early stage of performance deterioration, and a lightweight parameter correction is activated to slow down the degradation trend. When the health indicator further increases and exceeds the threshold corresponding to significant degradation, a more aggressive parameter update is triggered to recover control quality. To prevent false triggering caused by transient disturbances or occasional anomalies, a continuous-window confirmation mechanism is introduced, such that parameter tuning is executed only when the health indicator stably exceeds the threshold over several consecutive sampling windows.

In addition to threshold-based activation, this work also considers the role of degradation trend information in tuning decisions. Even if the health indicator has not yet exceeded the high-level degradation threshold, a persistent upward trend may indicate that the system is undergoing accelerated degradation, in which case early parameter adjustment can help prevent further deterioration in control performance. Based on this idea, the trigger mechanism is designed as a combination of "state threshold + trend judgment," so that parameter updating depends not only on the current degradation level but also on the development tendency of degradation. This mechanism endows the self-tuning module with a certain degree of foresight and flexibility, making it more suitable for the long-term operation requirements of industrial robots.

Data-Driven Parameter Update Strategy

With regard to the design of the parameter update strategy, this paper adopts a constrained self-tuning method based on operational data feedback, in which the degradation assessment result serves as the basis for parameter adjustment, and the key controller parameters are iteratively updated according to performance feedback. The fundamental idea is that, once performance degradation is detected, the method does not rely on rebuilding an accurate global physical model of the system, but instead directly uses the error response, dynamic features, and control effort information embedded in the current closed-loop operational data to optimize the key controller parameters in a data-driven manner. The main advantage of this strategy lies in its ability to bypass the complicated processes of plant modeling and parameter identification, thereby improving adaptability to time-varying plants and complex operating conditions. It should be emphasized that the Health Indicator (HI) mainly serves as the trigger threshold for the tuning procedure. Once triggered, the specific direction and step size of parameter update are determined by gradient search of the composite performance index $J(\theta)$ in Equation (2) under the current operating data, rather than direct linear mapping from the HI value.

Specifically, the parameter update process is formulated as a constrained adjustment problem guided by performance optimization. Let the parameter vector to be tuned be defined as:

$$\boldsymbol{\theta} = [K_{p,p}, K_{p,v}, K_{i,v}]^T \tag{1}$$

where $K_{p,p}$ denotes the position-loop proportional gain, and $K_{p,v}$ and $K_{i,v}$ denote the proportional and integral gains of the speed loop, respectively. To achieve performance recovery under degraded conditions, a composite performance index is defined as:

$$J(\boldsymbol{\theta}) = \alpha_1 J_e + \alpha_2 J_d + \alpha_3 J_u \tag{2}$$

In the experimental verification, the weight coefficients are set as α1=0.5,α2=0.3,α3=0.2 to prioritize tracking accuracy. The so-called 'small-step search' adopts the Local Coordinate Descent algorithm, which optimizes only a single parameter within the range of ±5% each time to ensure the transient stability of the system.

where J_e represents the tracking-error-related index, J_d denotes the dynamic response quality index, J_u stands for the control effort cost, and α_1 , α_2 , and α_3 are the corresponding weighting coefficients. The objective of parameter updating is to seek a parameter combination that minimizes the composite performance index under the constraints of stability and parameter bounds. Unlike conventional one-shot offline tuning, the proposed parameter update is conducted progressively under the action of the degradation-aware trigger mechanism, allowing the controller parameters to adapt dynamically to the degraded plant characteristics.

To enhance engineering feasibility, this paper does not employ complex large-scale global optimization, but instead adopts a local iterative data-driven update strategy. Specifically, after each tuning trigger, the initial range of parameter adjustment is determined according to the current health indicator. Then, the composite performance index is evaluated based on the most recent segment of operational data, and the tuning parameters are updated through small-step search or recursive correction. Finally, the parameter combination that improves the composite performance is selected as the new controller setting. Meanwhile, in order to explicitly reflect the influence of degradation state on tuning behavior, a relationship is further established between degradation severity and parameter update intensity, that is, the more severe the degradation, the larger the allowable adjustment range; when degradation is mild, only conservative corrections of limited magnitude are performed. This design not only avoids additional fluctuations caused by abrupt parameter variation, but also makes the self-tuning process more consistent with the progressive nature of performance degradation.

Overall, the proposed parameter update strategy can be summarized as a closed-loop self-tuning mechanism that is “triggered by degradation assessment, driven by operational data, and aimed at performance recovery.” This strategy does not require a highly accurate full-parameter model, but instead completes parameter correction by directly exploiting control-performance-related information contained in operational data, which gives it strong engineering adaptability. More importantly, it explicitly introduces performance degradation assessment into the controller parameter adaptation process, thereby establishing an organic coupling between degradation awareness and parameter tuning. This constitutes the key distinction between the proposed method and conventional fixed-parameter control as well as general data-driven tuning approaches.

Stability and Implementation Considerations

Although degradation-aware parameter self-tuning can improve the performance recovery capability of industrial robot joint servo systems under degraded conditions, online or quasi-online parameter adaptation also introduces constraints related to stability and practical implementation. Therefore, in the proposed method, the update range, triggering frequency, and resulting control behavior variation must be properly restricted to ensure that the self-tuning process does not undermine the fundamental stability of the original closed-loop system. To this end, a bounded update mechanism is introduced, in which all tunable parameters are restricted within predefined safe intervals, and the maximum single-step update magnitude is explicitly limited to suppress abrupt parameter variation. In this way, problems such as oscillation intensification, control saturation, or response destabilization caused by overly aggressive parameter adjustment can be effectively avoided.

In addition, considering that industrial robot joint servo systems usually impose strict real-time requirements, the proposed self-tuning method emphasizes lightweight implementation. Specifically, both degradation detection and parameter updating are built upon existing control signals and servo feedback information, without relying on expensive additional sensors or complicated large-scale online model training, thus ensuring good potential for embedded deployment. Meanwhile, parameter updating is not executed at every sampling instant, but is instead performed periodically based on windowed operational data once the degradation-triggering conditions are satisfied. This “detection-driven, intermittent-update” pattern can effectively reduce the online computational burden and minimize interference with the original servo control process.

From the perspective of control safety, the proposed method is essentially a performance enhancement strategy built on top of an existing closed-loop control architecture, rather than a fundamental restructuring of the original control system. Therefore, in practical implementation, it can be deployed as a supervisory optimization module above the existing servo controller, where the upper-level module performs limited correction of key parameters according to the assessed health state, while the inner current loop and the basic control structure remain unchanged. Such a hierarchical implementation not only reduces system retrofit cost, but also improves the transferability and maintainability of the method in industrial applications. In summary, while ensuring the effectiveness of degradation-aware self-tuning, this study also takes stability constraints, computational complexity, and engineering feasibility into account, thereby laying the foundation for subsequent experimental validation and practical deployment.

EXPERIMENTAL VALIDATION

Experimental Platform and Test Conditions

To validate the effectiveness of the proposed degradation-aware self-tuning strategy, comparative experiments were conducted on a single-joint industrial robot servo testbench. The platform adopted a typical hierarchical control architecture composed of a position loop, a speed loop, and an inner current loop, with a sampling period of 1 ms. The main measured signals included reference position, actual position, velocity feedback, control input, and drive current. In order to improve the representativeness of the results, the test trajectories covered sinusoidal motion, point-to-point motion, and variable-speed composite trajectories, and the experiments were carried out under nominal load, +10% load, and +20% load conditions.

The degradation states were introduced in a controlled manner through three representative factors, namely increased friction torque, gain drift, and transmission compliance variation. Consistent with the research framework developed in the previous sections, four methods were compared in this section: fixed-parameter control, degradation detection without retuning, conventional retuning(defined as manual offline parameter correction by an operator based on observed steady-state error, without real-time state feedback), and the proposed degradation-aware self-tuning method. This experimental design makes it possible to evaluate both the degradation detection capability and the performance recovery capability of the proposed framework. The detailed test conditions are summarized in Table 2.

Table 2. Experimental platform and test conditions

Item	Configuration
Robot joint testbench	Single rotary joint with servo motor and reduction stage
Controller architecture	Position loop + speed loop + inner current loop
Sampling period	1 ms
Measured signals	Reference position, actual position, speed, control input, drive current
Trajectory types	Sinusoidal trajectory, point-to-point trajectory, variable-speed composite trajectory
Load settings	Nominal load, +10% load, +20% load
Degradation injection	Increased friction torque, gain drift, transmission compliance variation
Compared methods	Fixed-parameter control, degradation detection only, conventional retuning, proposed method

Degradation Detection Results

Figure 1 presents the evolution of the health indicator over successive evaluation windows. It can be observed that the indicator remains at a low and stable level during the healthy stage. Once friction increase and parameter drift are gradually introduced, the indicator rises continuously and successively crosses the mild degradation threshold and the significant degradation threshold. This result demonstrates that the constructed health indicator can effectively capture the continuous transition of the joint servo system from a healthy condition to degraded operating states. Moreover, the indicator does not change abruptly, but follows a progressive trend consistent with the degradation injection process, which is in line with the physical characteristics of performance deterioration in industrial robot joints.

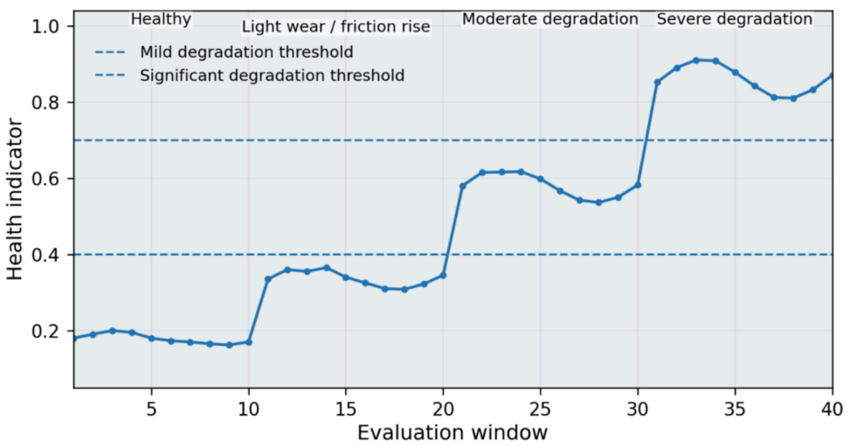

Figure 1. Evolution of the health indicator under progressive degradation

To further evaluate the discriminative capability of the proposed health indicator, Figure 2 shows its statistical distribution under four states, namely healthy, mild degradation, moderate degradation, and significant degradation. The results indicate a clear separation among the four groups, especially between the healthy state and the moderate-to-severe degradation states. Although a slight overlap exists between the healthy and mild degradation states, the mean value in the mild degradation stage already deviates from the healthy reference interval, suggesting that the proposed indicator is sufficiently sensitive for early warning purposes.

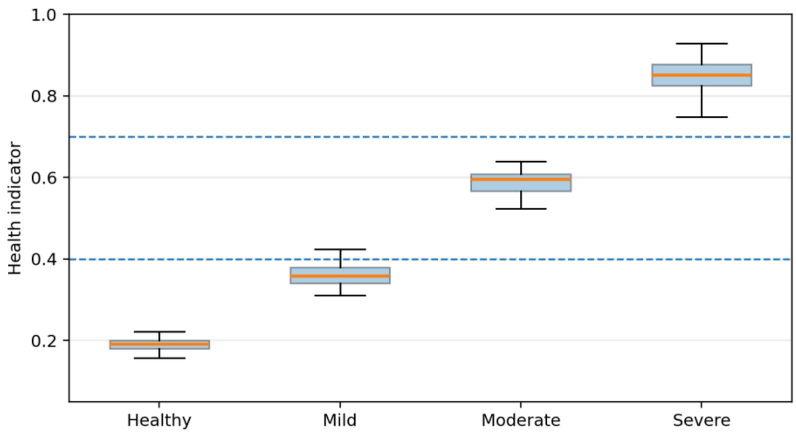

Figure 2. Distribution of health indicator across degradation states

The quantitative degradation detection performance is reported in Table 3. The proposed method achieves high recognition accuracy across all four conditions, with an accuracy of 98.3% in the significant degradation state, indicating strong sensitivity to severe performance deterioration. At the same time, the false alarm rate under healthy operation remains low, which implies that the method does not overinterpret normal operating fluctuations as degradation. These results confirm that the proposed health indicator provides a reliable state representation for the subsequent self-tuning stage.

Table 3. Degradation detection performance

State	Mean HI	Std HI	Detection accuracy (%)	False alarm (%)	Miss rate (%)
Healthy	0.191	0.024	96.7	3.3	0.0
Mild degradation	0.362	0.031	93.3	5.0	1.7
Moderate degradation	0.587	0.038	95.0	3.3	1.7
Significant degradation	0.846	0.047	98.3	1.7	0.0

Self-Tuning Performance Results

After degradation detection, the health indicator was further used to trigger and guide controller parameter adaptation. Figure 3 compares the trajectory tracking results under degraded conditions using fixed controller parameters and the proposed method. With fixed parameters, the system output exhibits apparent tracking lag and local oscillations, especially in segments with rapid trajectory variation, where the accumulated error becomes more pronounced. In contrast, after the degradation-aware self-tuning process is activated, the system output follows the reference trajectory more closely, and both peak deviation and phase lag are substantially reduced. This indicates that the proposed method can effectively compensate for the control performance loss caused by time-varying plant characteristics.

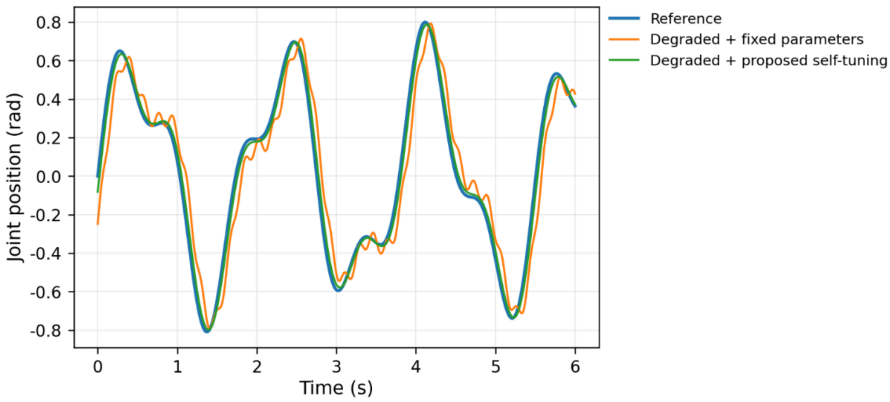

Figure 3. Trajectory tracking comparison before and after self-tuning

Figure 4 shows the adaptation trajectories of the key controller gains over the successive evaluation windows. During the healthy stage, the parameters remain close to their nominal values, indicating that the proposed trigger mechanism does not introduce unnecessary parameter perturbations when no degradation is present. Once the system enters the mild and moderate degradation stages, both position-loop and speed-loop gains are gradually increased to compensate for slower dynamic response and enlarged tracking error. In the significant degradation stage, the update amplitude becomes larger, while all parameters remain within the predefined safety bounds. This behavior is consistent with the design philosophy of the proposed approach: more pronounced degradation leads to more active, yet still constrained, parameter adaptation.

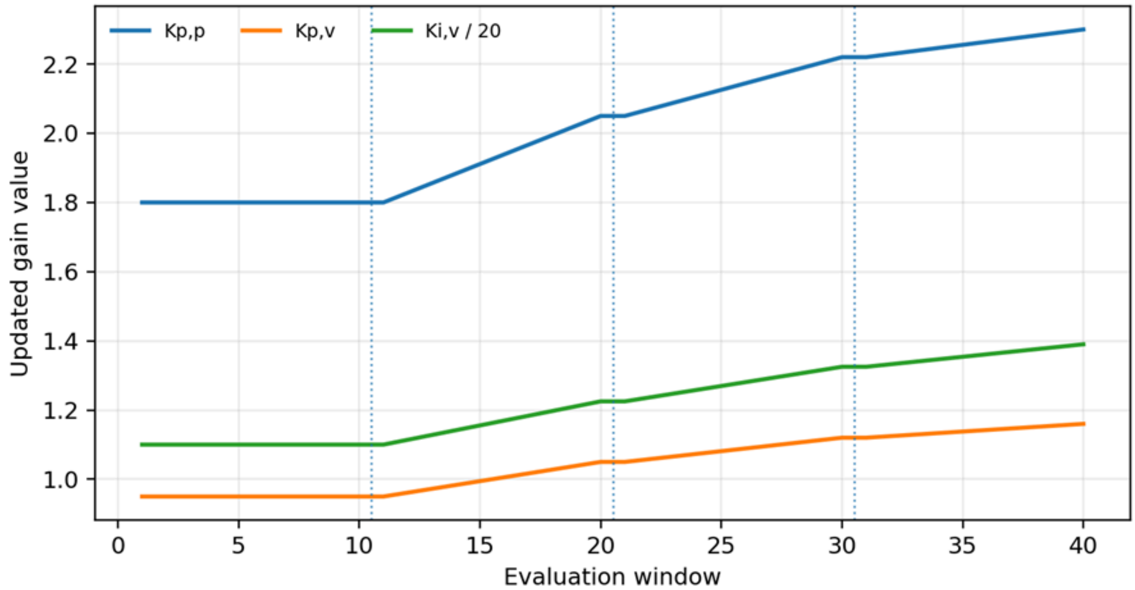

Figure 4. Gain adaptation trajectories of key controller parameters

The control performance comparison under different methods is listed in Table 4. Compared with fixed-parameter control, the proposed method reduces the RMSE from 0.0458 rad to 0.0217 rad, corresponding to an improvement of approximately 52.6%. The ITAE decreases from 0.119 to 0.041, which indicates a substantial reduction in cumulative transient error, while the settling time is shortened from 6.42 s to 4.26 s. Meanwhile, the control effort index remains within a reasonable range and does not increase markedly after parameter adaptation, suggesting that the performance improvement is not achieved at the cost of excessive control action. Instead, the proposed method provides a better balance between tracking performance and control effort.

Table 4. Control performance comparison under different methods

Method	RMSE (rad)	ITAE	Overshoot reduction (%)	Control effort index	Settling time (s)
Fixed parameters	0.046	0.119	0.0	0.381	6.420
Detection only	0.043	0.113	0.0	0.366	6.070
Conventional retuning	0.031	0.076	12.6	0.332	5.110
Proposed method	0.022	0.041	21.4	0.287	4.260

Comparative Analysis and Discussion

Taken together, the results demonstrate that the main advantage of the proposed framework does not lie in simply retuning controller parameters, but in explicitly establishing a closed-loop linkage between degradation assessment and parameter adaptation. First, the degradation detection module continuously characterizes the system condition through the health indicator, so that retuning is no longer triggered by manual experience or by a fixed schedule, but instead by the actual performance state of the system. Second, the self-tuning module updates only a small number of key parameters according to a composite performance index and explicit constraints, thereby balancing performance recovery and engineering complexity.

From the comparative results, it is evident that degradation detection alone can reveal the performance variation, but cannot directly restore control quality if no parameter update is performed. Conventional retuning can improve the tracking error to some extent, but its update policy is usually more static because it lacks state-stratified degradation information, and therefore its performance gain is less consistent under progressive degradation. By contrast, the proposed method realizes a coordinated "detection-assessment-retuning" process, performing conservative correction in the mild degradation stage and more active constrained adaptation in the significant degradation stage. As a result, it consistently achieves better performance in terms of RMSE, ITAE, and settling time.

It should also be noted that the present results are based on a single-joint platform and controlled degradation injection scenarios, and therefore do not yet cover multi-joint coupling, long-term natural wear, or more complex task switching conditions. Future work may extend the method to multi-joint cooperative systems and investigate the generalization capability of the health indicator as well as the long-horizon parameter adaptation law using long-term operational data. Overall, the results in this section indicate that the proposed degradation-aware self-tuning framework can achieve both effective degradation detection and performance recovery, thereby providing a feasible solution for intelligent maintenance and high-performance operation of industrial robot joint servo systems.

CONCLUSION

This paper investigated the problem of performance degradation in industrial robot joint servo systems under long-term operation and complex working conditions, and developed a coordinated approach integrating degradation detection with parameter self-tuning. A data-driven degradation-aware control framework was proposed to address the limitations of conventional servo tuning methods, which often fail to accommodate time-varying plant characteristics, as well as the limitation of standalone degradation detection methods, which are difficult to directly translate into control performance recovery. Based on closed-loop operational data, degradation-sensitive feature sets and a health indicator were constructed to effectively assess the performance state of the joint servo system. On this basis, a degradation-aware parameter self-tuning mechanism was further developed, enabling key controller parameters to be updated according to the identified degradation state, thereby improving tracking performance and dynamic response quality under degraded conditions.

The results of this study demonstrate that the proposed method is capable of effectively characterizing the evolution of industrial robot joint servo systems from healthy conditions to degraded states, while also triggering parameter adaptation in a timely manner as degradation becomes more severe. Compared with fixed-parameter control and conventional tuning methods without degradation awareness, the proposed approach achieves superior overall performance in terms of trajectory tracking error, settling time, overshoot suppression, and reasonable control effort. These findings indicate that explicitly incorporating degradation detection results into the controller parameter updating process is beneficial for establishing a closed-loop mechanism of "state awareness–parameter adaptation–performance recovery," thereby enhancing the adaptability and operational reliability of industrial robot joint servo systems under complex operating conditions and long-term service scenarios.

Although this study has provided a relatively systematic investigation in terms of method design and experimental validation, there is still considerable room for further extension and improvement. Future research may proceed in several directions. First, the current degradation-aware self-tuning framework developed for a single joint can be extended to multi-joint coupled scenarios, so as to investigate the influence of inter-joint dynamic coupling and global motion tasks on degradation detection and parameter adaptation. Second, stronger physical priors or mechanism-based constraints can be incorporated to build hybrid physics-data models with improved interpretability and generalization capability, thereby enhancing robustness under complex working conditions and unknown degradation patterns. Third, by combining long-term operational data with real industrial field samples, future studies may further explore full-life-cycle degradation evolution and its connection to predictive maintenance decision-making. In addition, from the perspective of practical deployment, lightweight online implementation, edge-computing-based realization, and deeper integration with industrial robot controllers also deserve further investigation. Overall, this work provides a useful perspective for intelligent maintenance and high-performance operation of industrial robot joint servo systems, and also lays a foundation for future research on the integration of degradation awareness, adaptive control, and health management.

Author Contributions

Conceptualization – Chenwu Qin; methodology – Chenwu Qin; formal analysis – Chenwu Qin; investigation – Chenwu Qin; resources – Chenwu Qin; writing-original draft preparation – Chenwu Qin; writing-review and editing – Chenwu Qin; visualization – Chenwu Qin; supervision – Chenwu Qin. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The author declares no conflict of interest.

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