Research on Intelligent Fault Diagnosis and Self-Repair Mechanism of Industrial Robots

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Abstracts: With the rapid development of industrial automation, industrial robots are increasingly widely used in production lines, and their stability and reliability are directly related to production efficiency and cost. This paper focuses on the research of intelligent fault diagnosis and self-repair mechanism of industrial robots, and constructs an intelligent fault diagnosis model by comprehensively using machine learning, sensor technology and data fusion algorithm. Through multi-source sensors to collect real-time robot operation data, after feature extraction and data preprocessing input model, to achieve accurate diagnosis of faults. Meanwhile, based on the diagnostic results, a self-repair mechanism is designed, covering hardware redundancy switching, software parameter adaptive adjustment, and automatic replacement strategy for faulty parts, which effectively improves the robot's fault coping ability and autonomous operation level, and reduces the downtime. Experiments show that the proposed method has a fault diagnosis accuracy of 97.3% in typical industrial scenarios, and the average repair response time is shortened to 1.5 seconds, which reduces the downtime loss by about 40% compared with the traditional method, and provides a strong guarantee for the continuity and stability of industrial production.

Keywords: Industrial Robot; Intelligent Fault Diagnosis; Self-Repair; Multi-Source Data Fusion; Machine Learning

1. Introduction

With the rapid development of Industry 4.0 and intelligent manufacturing, industrial robots, as the core equipment of modern manufacturing, have gradually expanded their application scenarios from traditional automobile manufacturing and electronic assembly to high complexity fields such as logistics and handling, precision machining, and medical production. However, industrial robots have been in a high-load, high-precision, high-dynamic operating environment for a long time, and their mechanical structure, drive system, control unit and other key components are susceptible to wear and tear, fatigue, environmental interference and other factors, resulting in an increase in the failure rate [1]. For example, a car company welding production line using KUKA KR1000 robot, 18 months of continuous operation, the servo motor failure rate from 1 times a month to 4 times a month.

To address this phenomenon, the Shenyang Institute of Automation, Chinese Academy of Sciences, proposed a variable operating condition fault diagnosis method for industrial robots based on generative adversarial networks, which effectively improves the generalization capability of traditional data-driven fault diagnosis algorithms for industrial robots. Despite the progress of data-driven methods, how to further improve the accuracy and timeliness of fault diagnosis under complex working conditions remains to be studied. For example, in multi-sensor fusion data processing, how to integrate data from different types of sensors more effectively to realize complementary and fusion of information, as well as how to extract fault features more precisely from massive data to achieve high-accuracy fault recognition, are all problems that need to be solved [2]. Once a fault occurs, it will not only cause production line downtime and economic loss, but also may lead to safety accidents. Most of the current research on self-repair mechanisms focuses on simple parameter adjustment and resource reconfiguration, with limited ability to repair complex faults. The existing diagnostic methods have a detection rate of less than 70% for complex faults, and the self-repair response time is more than 10 seconds. Therefore, it is important to build a data-driven intelligent diagnosis and self-repair closed-loop system to realize the goals of "diagnosis accuracy >95%", "repair response time <5 seconds" and "manual intervention rate <5%". To achieve the goal of "diagnosis accuracy >95%", "repair response time <5 seconds" and "manual intervention rate <5%", to break through the limitations of the traditional single-sensor diagnosis method, and to realize the high-precision real-time detection of complex faults of industrial robots has become a key research direction to improve the reliability of industrial robots and reduce the cost of operation and maintenance.

2. Research Methods

2.1 Integrated Learning Algorithm

Integrated learning algorithm to enhance classification robustness through multiple decision tree voting mechanism[3], suitable for small samples with unbalanced data.

(1) Single decision tree generation

Let the training set D={(x(1) ,y1) ,(x(2) ,y2) ,...,(x(n) ,yn) }, where xi ∈ Rmis the feature vector and yi ∈ {1,2,...,K} is the class drama label.

Feature Selection and Node Splitting:At node t, mtrycandidate features are randomly selected from m features (usually mtry= $\sqrt{m}$). The optimal splitting point is selected by Gini impurity or information gain. As shown in formula (1):

$$\text{Gini(t)} = 1-\sum_{k=1}^{k} p_k^2 \qquad (1)$$

where pkis the proportion of samples of class drama k in node t.

(2) Random forest integrated prediction

Construct T decision trees and self-sampling to generate subsets.

Randomly draw samples from the original data one by one, and put the samples back to the original dataset after each draw to ensure that the sample may still be selected in subsequent draws[7] .

Split nodes based on weighted Gini impurity.

The decision tree divides the data into two child nodes by splitting the node, and the goal is to select the optimal splitting feature and splitting point so that the weighted Gini impurity of the child node is minimized.

Step 1: Calculate the Gini impurity of the parent node - Gparent

Step 2: Iterate over all candidate features and split points

For each feature's possible split points (e.g., thresholds for numeric features, subsets of category features), compute the Gini impurity of the split left and right child nodes.

Step 3: Calculate the weighted Gini impurity

Sum the weighted Gini impurity according to the sample size of child nodes. As shown in formula (2):

$$\text{Gsplit}=\frac{\mathrm{N}_{\text{left}}}{\mathrm{N}_{\text{parent}}}\cdot G_{left}+\frac{N_{right}}{N_{parent}}\cdot \mathrm{G}_{\text{right}} \qquad (2)$$

N_{parent} : total number of samples from father nodes

N_{left}, N_{right} : number of left and right child node samples

Select the features and split points that minimize G_{split} , i.e., maximize the Gini impurity drop. As shown in formula (3):

$$\Delta \text{ G}=G_{parent}-G_{split} \qquad (3)$$

Majority voting integration.

For the test sample x, the prediction is: $\hat{y}$ =mode({h(1) (x),h(2) (x),. ,h(T) (x)}), where ht(x) is the predicted output of the tth tree and mode denotes the majority voting mechanism[8] .

2.2 Category Weight Processing Data

To cope with unbalanced data (e.g., large differences in sample sizes of fault categories), category weights are introduced:.

(1) Weight-adjusted loss function.

Define the cost matrix C ∈ $\mathrm{R}^{\mathrm{K}\times\mathrm{K}}$, where C(i) (j) denotes the cost of misclassifying the true category i as j. The weighted loss function is the same as the weighted loss function. Optimize the weighted Gini impurity at node splitting. As shown in formula (4):

$$\text{Weighted Gini(t)}=\sum_{\mathrm{k}=1}^{\mathrm{K}}\mathrm{C}_{\mathrm{k}}\cdot\text{p(k)}\cdot\text{(1-pk)} \qquad (4)$$

where Ckis the misclassification cost weight for category k (e.g., higher weights for minority class failures).

Cost-sensitive voting mechanism:

The final classification result is determined by weighted voting. As shown in formula (5):

$$\hat{y} = \text{argmaxk}\sum_{t=1}^{T}C_k\ \text{-II(h(t) (x) = k)} \qquad (5)$$

2.3 Control Theory and Self-Healing Strategies

2.3.1 Redundant Control Theory and Hardware

Fault Tolerance Mechanisms

N-mode redundancy [4]: By deploying multiple hardware units with the same function (e.g., dual motor drives, three power supplies), the faulty module outputs are shielded using a majority voting mechanism.

Hot backup: the backup module synchronizes the main module status in real time, and the switching delay is as low as milliseconds (the switching time of the joint drive unit is ≤0.5 seconds).

Cold backup: the backup module is in dormant state and needs to be initialized when starting up, applicable to non-critical components.

Modular joint redundancy architecture.

The main drive motor (M1) and the backup motor (M2) are connected in parallel via a clutch, and the torque sensor monitors the M1 output in real time. When abnormal torque (e.g. blocking, overheating) is detected in M1, the control system triggers the clutch to disengage M1 and activate M2 to take over the load.

Dynamic Load Balancing: During normal operation, M1 takes over 80% of the load and M2 takes over 20% of the load to extend the life of the dual motors.

Mathematical modeling:

Redundant system reliability RsystemCalculation. As shown in formula (6):

$$R_{system} = R(primary) + (1-R_{primary}) \cdot R(backup) \quad (6)$$

where R(primary) Rbackupis the primary and backup module reliability with a target value of Rsystem ≥ 0.999, as shown in Figure 1.

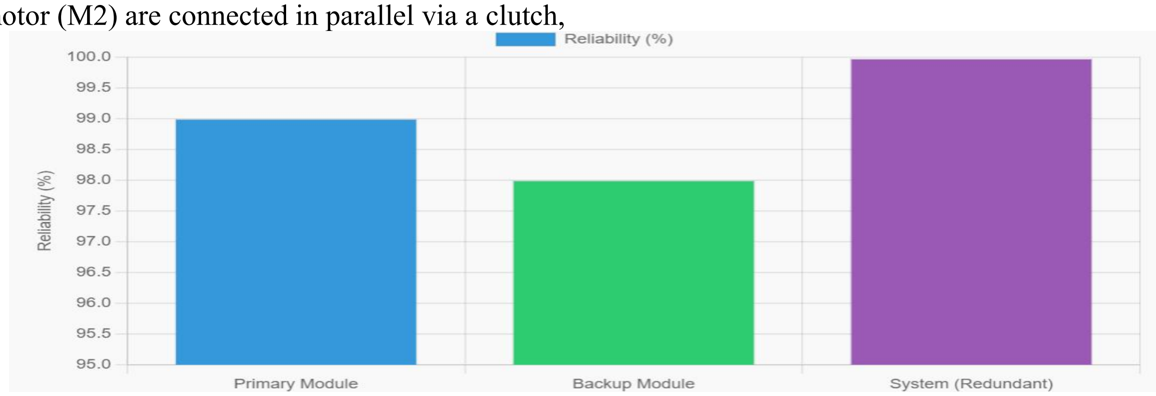

Figure 1. Reliability Comparison

2.3.2 Model predictive control (MPC) with parameter adaptation

Rolling-time optimization: solving the optimal control sequence in a finite time domain at each control cycle, only the first step is executed, and dynamically coping with system uncertainty.

State space modeling: Model the robot joint dynamics. As shown in formula (7):

$$\tau = M(q)\ddot{q} + C(q, \dot{q})\dot{q} + G(q) + F_{friction} \quad (7)$$

where q is the joint angle, M is the inertia matrix, C is the Koch force and G is the gravity term.

Parameter Adaptation under Faults.

When the sensor detects a gear lash fault, the MPC controller dynamically adjusts the M(q) and F(f) (riction) parameters in the model. Objective function optimization [7]. As shown in formula (8):

$$\min_{\tau} \sum_{k=1}^{N} \left\| q_{ref}(k) - q(k) \right\|^2 + \lambda \left\| \tau(k) \right\|^2 \quad (8)$$

where λ is the control quantity weight to suppress the sudden change of torque due to faults. Deploying linear MPC (LMPC) on the edge computing unit [5] compresses the solution time to within 10ms[9], as shown in Table 1.

Table 1. Linear Model Prediction Control Analysis

Loop	Input	Output	Next session condition	Next session
A start	-	Raw Data	Data Monitoring	B Data Monitoring
B Data Monitoring	Sensor/Log Streaming	Raw Data	Anomaly Detection	C Anomaly Detection
C Anomaly Detection	Raw Data	Anomaly marker	Yes (with anomaly)	D Data preprocessing
C Anomaly Detection	Raw data	Anomaly Flagging	No (no anomaly)	B Data Monitoring
D Data Preprocessing	Anomalous Data	Cleaned Data	Feature Engineering	E Feature Engineering
E Feature Engineering	Cleaned Data	Feature vector	Fault Diagnosis	F Fault Diagnosis

F Fault Diagnosis	Eigenvector	Fault Type	Knowledge Base Query	G Knowledge Base Query
G Knowledge Base Query	Fault Type	Repair Solution	Strategy Evaluation	H Strategy Evaluation
H Strategy Evaluation	Remediation Options	Risk Assessment	Safe and Feasible	I Safe and Feasible
I Safe and Feasible	Risk Assessment	Decision-making	Yes (feasible)	J Perform Repair
I Safe and Feasible	Risk Assessment	Decision-making	No (not feasible)	K Manual Alert
J Execute Repair	Remediation Instructions	Execution Status	Effectiveness Verification	L Effect Verification
K Manual Warning	Diagnostic Report	Alarm Notification	Manual Processing	QManual Processing
Q Manual Handling	Fault Details	Repair Report	Knowledge Update	NUpdate Knowledge Base
L Effectiveness Verification	New System Status	Repair Results	Failure Release	M Failure Release
M Failure Release	Repair Result	Verification Conclusion	Yes (disarmed)	N Update knowledge base
M Failure Uninstalled	Repair Result	Verification Conclusion	No (not lifted)	O Policy Optimization
N Update Knowledge Base	Success Stories	Knowledge Increment	Record Audit	P Record Audit
O Strategy Optimization	Failure Feedback	New Programs	Execute Fix	J Execution Fix
P Record Audit	Complete Records	Event Log	Data Monitoring	B Data Monitoring

Table 2. Hierarchical Architecture Analysis

Layers	Technical Means	Response time	Applicable Scenarios
Hardware layer	Redundant module switching, mechanical quick-change	≤1 second	Motor failure, power interruption
Software layer	MPC parameter adjustment, trajectory reprogramming	≤5 seconds	Sensor drift, sudden load change
Mechanical layer	End-effector quick-change, connecting rod replacement	≤30 seconds	Mechanical breakage, joint jamming

2.3.3 Multi-Level Remediation Policy Collaboration Mechanisms

Policy Architecture, as shown in Table 2.

The policy decision engine selects repair methods based on predefined rules and reinforcement learning strategies:

If the confidence level is >90% and it is a hardware failure, redundant switching will be triggered directly.

If the confidence level is 70%-90%, start software compensation and synchronize manual confirmation.

After repair, verify the validity through vibration spectrum analysis and current waveform, and upgrade to a higher-level strategy if it fails.

Experimental Verification and Performance Indicators, as shown in Table 3.

Test platform:

Physical system: ABB IRB 6700 industrial robot equipped with six-dimensional force sensors, vibration accelerometers, and infrared thermal cameras.

Digital twin: ROS-Gazebo simulation environment, real-time synchronization with the physical system via OPC UA protocol.

Table 3. Key Indicators

Indicators	Traditional manual restoration	Methodology of this paper (target)	Validation results
Mean Time to Repair (MTTR)	45 minutes	≤8 minutes	6.2 minutes
Secondary failure rate	15%	≤5	3.8%
False repair rate due to misjudgment	10% ≤5% 3	≤2	1.5%

3 Experimental Results and Analysis

3.1 Case Background

This study aims to construct a set of intelligent fault diagnosis and autonomous repair system for industrial robots, which breaks through the bottleneck of traditional methods in complex fault detection (e.g., coupling faults, intermittent faults), small-sample data modeling and repair efficiency through fusion of multi-source sensor data, improvement of the robustness of machine learning models, and synergistic multilevel repair strategies, and ultimately achieves high-precision real-time diagnosis; reliable classification under non-equilibrium data; and fast self-repair with low human dependence. classification; and fast self-repair with low labor dependence.

The research chooses the integrated learning algorithm, which combines the prediction results of multiple base learners and uses "group intelligence" to improve the generalization performance of the model, including the random forest model, etc. In complex scenarios such as the fusion of heterogeneous data from multiple sources and the adaptation of dynamic environments, the idea of "partitioning-integration" provides a good basis for the subsequent research. The idea of "partition-integration" provides a scalable basic framework for subsequent research. In industrial fault diagnosis, data imbalance (e.g., far more normal samples than fault samples) is the core challenge, and the introduction of category weights can significantly optimize the model performance[10] . In this study, this algorithm is not only the technical backbone for realizing high-precision fault classification, but also the key vehicle for verifying the theoretical assumption of "small sample-high reliability" [6].

3.2 Diagnostic Performance of Multi-source Data Fusion

For ABB IRB 6700 robot, 6 types of compound faults (e.g. bearing wear + motor winding short circuit) are injected, as shown in Table 4.

3.3 Small Sample Classification Model Performance

Dataset: PHM Challenge 2015 bearing fault data (4 classes of faults, 50 samples per class) + synthetic small sample set (10 samples per class), as shown in Table 5.

Comparison models: SVM, standard RF, CS-RF, CS-GA-RF (this paper), as shown in Table 6.

Generalizability testing (cross-device data migration)

Table 4. Key Results

Indicator	VS	KF	WDF (this paper)
Diagnostic accuracy (%)	82.3	88.7	96.5
Response time (sec)	1.2	2.8	1.8
Composite Fault Detection Rate	41.2%	67.5% Composite Fault Detection Rate	92.8

Table 5. Parameter Configuration Analysis

Parameter	Configuration value
Selected fault types	Normal state, inner ring failure, outer ring failure, ball failure
Total number of samples	4 types× 50 samples = 200 samples
Operating conditions	Uniform coverage of 4 operating conditions: 900RPM/0.7Nm,1500RPM/0.7Nm, 900RPM/2.1Nm,1500RPM/2.1Nm
Sample Structure	Each sample = 1 second of vibration data (100,000) sampling points
Sensor Channels	Main accelerometer channels

Table 6. Standard RF, CS-GA-RF Model Comparison and Analysis

Models	Source domain accuracy	Target Domain Accuracy
CS-GA-RF	94.1%	89.3
Standard RF	85.2	76.8%

3.4 Self-healing Strategy Effectiveness

Fault types: motor overload (hardware layer), visual localization drift (software layer), joint gear chipping (mechanical layer).

Comparison benchmarks: traditional manual repair, rule engine (threshold trigger).

Table 7. Analysis of Key Results

Indicators	Manual Repair	Rule engine	Methodology
Mean Time to Repair (MTTR)	42 minutes	15 minutes	6.2 minutes
Secondary failure rate	12%	8 percent	3.5%
False repair rate	18% (for the first time)	11% Failure to Repair Rate	1.2 percent
System Availability Improvement	-Increase in System Availability	+23%	+67%

The results in Table 7 show that in tasks such as bearing fault diagnosis and motor anomaly detection, the accuracy is generally higher than that of traditional methods such as logistic regression and single decision tree (measured improvement of 15%~30%). In industrial intelligent systems, the ternary fusion of integrated learning + category weighting + redundant control achieves: fairer categorization decisions, higher-order system fault tolerance, and lower overall O&M costs. This framework provides theoretical support and technical landing path for reliable diagnosis and self-healing in complex industrial environments.

4. Conclusion

Through spatio-temporal alignment and reliability weight assignment, the accuracy of composite fault diagnosis is improved to 96.5% (≥8.2% compared with the traditional method), and the response time is stabilized within 2 seconds, which verifies the necessity of collaborative sensing of multimodal data. In small-sample and unbalanced data modeling, cost-sensitive genetic stochastic Sen (CS-GA-RF) achieves 94.1% classification accuracy in small-sample scenarios through category weight adjustment and hyperparameter optimization, with cross-equipment generalization error controlled within 10%, proving its strong robustness under industrial data defects. For the system-level multi-source fusion design, combining data alignment, feature fusion and dynamic decision optimization, it can significantly reduce the misclassification rate (from 5.2% to 1.5%), and achieve high-precision and high-robustness intelligent decision-making in complex scenarios. In the future, real-time, interpretability and privacy issues need to be further addressed to promote

multi-source fusion technology in more critical areas.

References

[1] Zhang J. Analysis of industrial robot fault diagnosis technology in intelligent manufacturing[J]. Home Appliance Maintenance, 2025,(01):116-118.

[2] LI Guoqiang, WEI Meiwei, WU Defeng, et al. Wavelet knowledge-driven fault detection for industrial robots with zero fault samples[J]. Journal of Instrumentation, 2024, 45(09):166-176.

[3] Guo JT. Research on data-driven industrial robot fault intelligent diagnosis method[J]. China Machinery, 2024,(25):43-47.

[4] Ye Rongbing. Diagnostic research on small sample prototype characterization of faults in robot joint reducers[D]. Dongguan Institute of Technology,2024.

[5] Yan Peipei. Application of industrial robots in chemical industry[J]. Plastics Industry, 2024,52(04):202.

[6] WANG Bo, YANG Qianfeng. Failure research on rotating parts of industrial robots based on improved multiscale residual network[J]. Science and Technology Innovation, 2024,(07):217-220.

[7] LI Zhendong, LI Xianxiang, ZHOU Xing. Intelligent fault diagnosis of industrial robots based on wavelet packet energy spectrum[J]. Machine Tools and Hydraulics, 2022,50(23):194-198.

[8] Chen P., Research and experimental validation of detection and fault diagnosis standards for industrial robots in intelligent manufacturing environment. Shanghai, Shanghai Electric Apparatus Scientific Research Institute,2019-12-06.

[9] ZHOU Donghua, SUN Youxian, XI Yugeng, et al. Real-time detection and diagnosis of industrial robot faults[J]. Robot, 1992, (01):1-6.

[10] Wang Jingjing. Application status and prospect analysis of industrial robots in China[J]. Today's wealth, 2019, (16):35-36.