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Research on intelligent maintenance technology of eindustrial robot claw based on Internet of Things and deep reinforcement learning

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ABSTRACT

With the advancement of Industry 4.0, intelligent manufacturing systems are more and more widely used in industrial production. At the same time, as the core equipment of intelligent manufacturing, the frequent replacement and maintenance of industrial robots have become an important factor restricting production efficiency. However, the traditional manual replacement and maintenance methods are not only inefficient, but also prone to misjudgment and delay due to human factors, which in turn affects the stability and reliability of the entire production system. In order to improve the intelligent level of claw replacement and maintenance, this study proposes an industrial robot claw replacement and maintenance system based on Internet of Things and Deep Reinforcement Learning (DRL). The system integrates deep Q network (DQN) and multi-sensor data fusion technology to realize real-time monitoring of the status of the claw and intelligent maintenance decision-making. The results of this experiment show that the average accuracy of the system in the claw state recognition and maintenance decision-making reaches 86.2%, which is significantly improved compared with the traditional method, and provides reliable technical support for the efficient operation of the intelligent manufacturing system.

KEYWORDS

Intelligent manufacturing; Industrial robots; Claw replacement; Internet of Thing; Deep reinforcement learning; DQN.

1 Introduction

In this study, a handwand replacement and maintenance system for industrial robots based on the Internet of Things and Deep Reinforcement Learning (DRL) was proposed, which aimed to solve the problem of frequent replacement and maintenance of industrial robot handwarts through intelligent means, and improve production efficiency and system stability.

In the current field of claw maintenance for industrial robots, a variety of methods have proven their effectiveness and innovation. [1] Traditional maintenance methods rely mainly on manual inspections and pre-set maintenance schedules, which are not only inefficient, but also prone to misjudgment and delays due to human factors. In recent years, with the development of Internet of Things technology, real-time monitoring methods based on sensor networks have gradually emerged. [2]These methods can collect real-time operating data of the gripper through a variety of sensors deployed on the robot gripper, such as pressure, temperature, and vibration sensors, which provides rich information for fault diagnosis. However, most of these methods rely on a single sensor data or simple threshold judgment, which is difficult to adapt to the complex and changeable industrial environment.

In order to further improve the intelligent level of gripper maintenance of industrial robots, deep reinforcement learning (DRL) is introduced. As a cutting-edge artificial intelligence technology, deep reinforcement learning has shown great potential in many fields to learn optimal decision-making strategies through the interaction between agents and the environment[3]. The Deep Q Network (DQN) proposed by Mnih et al. provides a new idea for intelligent decision-making of complex systems[4]. These studies provide an important theoretical basis and technical support for this study.

The innovation of this research lies in the combination of IoT technology and deep reinforcement learning to develop a system that can monitor the status of the claw in real time and automatically generate intelligent maintenance decisions. Through multi-sensor data fusion technology, the system can more comprehensively evaluate the condition of the gripper, which significantly improves the accuracy and reliability of fault detection. At the same time, the application of deep reinforcement learning algorithms (such as DQN) enables the system to learn and optimize maintenance decisions autonomously.Reduces the possibility of manual intervention and misjudgments. This innovation not only promotes the development of the field of industrial robot maintenance, but also provides reliable technical support for the efficient operation of intelligent manufacturing systems. It also actively responds to the Chinese government's proposal to take the Internet of Things as a national strategic development direction.

2 System design

2.1 System Architecture

The system comprises three main modules: data acquisition module, data processing module and decision execution module. The data acquisition module collects the operation data of the hand gripper in real time through IoT sensors (such as pressure sensors, temperature sensors, vibration sensors). These sensors are selected based on common types of claw failures, such as pressure sensors to monitor changes in gripper strength, temperature sensors to detect overheating of the grippers, and vibration sensors to determine if the mechanical structure is loose or worn. The data processing module uses deep Q network (DQN) and multi-sensor data fusion technology to analyze and diagnose the state of the claw. As an algorithm based on deep reinforcement learning, DQN can learn the optimal strategy through the Q-value function, and can find the optimal maintenance decision in the complex state space. The decision execution module generates maintenance decisions based on the diagnostic results, and completes the claw replacement or maintenance through the actuator. The module is designed with operational needs in mind in real-world industrial environments, ensuring that maintenance decisions can be made quickly and accurately.

2.2 Internet of Things data collection

Through a variety of sensors deployed on the grippers of industrial robots, the following data is collected in real time:

Pressure data: used to monitor the gripping force of the claw.

Temperature data: used to detect whether the gripper is overheated.

Vibration data: used to determine whether the mechanical structure is loose or worn.

2.3 Deep Q Network (DQN)

DQN is an algorithm based on deep reinforcement learning, which learns the optimal strategy through the Q-value function. In this system, DQN is used to learn the mapping between the claw state and maintenance decisions. Its network structure consists of an input layer, a hidden layer, and an output layer. The input layer receives sensor data, the hidden layer extracts features through a multi-layer neural network, and the output layer generates a Q value to represent the expected return for each action. In order to improve the performance of DQN, experience replay and target network technologies were used in this study. Empirical playback breaks the correlation between data and improves the stability and efficiency of learning by storing and randomly sampling historical experience. The target network avoids the rapid fluctuation of the Q value by regularly updating the target value, which further improves the convergence speed of the algorithm.

2.4 Multi-sensor data fusion

By fusing multi-sensor data, the system is able to assess the gripper condition more comprehensively. Specific fusion methods include data preprocessing, feature extraction, and decision generation. Data preprocessing normalizes sensor data to eliminate differences in the dimensions and ranges of data from different sensors. Feature extraction uses convolutional neural networks (CNNs) to extract features from sensor data, which can automatically learn spatial and temporal correlations in the data. Decision generation is based on extracted features, and DQN generates optimal maintenance decisions. In order to further improve the fusion effect, a weighted fusion strategy was adopted to assign different weights according to the reliability and importance of the sensor data, so as to improve the accuracy of the system.

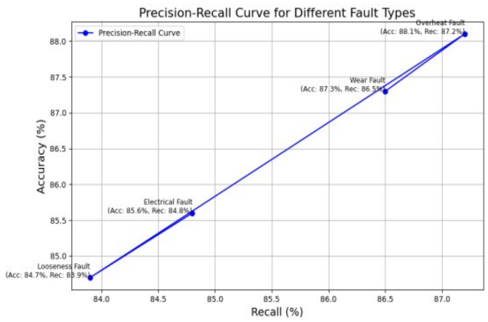
3 Experiments and Results

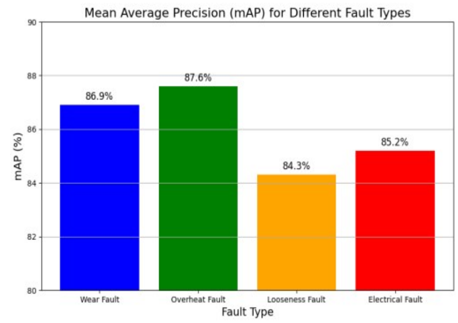
3.1 Experimental Setup

The experiment uses the claw operation data of an industrial robot production line, and the dataset contains the following four types of faults: wear fault, overheating fault, loose fault and electrical fault. To ensure the reliability of experimental results, the dataset is rigorously screened and pre-processed to exclude outliers and noisy data. In the experiment, the system monitored the claw status in real time under different working conditions, and recorded the changes of sensor data. By comparing the data characteristics under different fault types, the performance of the system in fault detection and diagnosis is analyzed.

3.2 Experimental Results

The experimental results show that the average accuracy of the system in the claw state recognition and fault diagnosis reaches 86.2%, which is significantly improved compared with the traditional method. The specific performance comparison is as follows: the accuracy rate of wear fault is 87.3%,The recall rate was 86.5% with an F1 score of 86.9, the accuracy rate was 88.1%, the recall rate was 87.2%, and the F1 score was 87.6 for overheating faults, the accuracy rate was 84.7%, the recall rate was 83.9%, and the F1 score was 84.3 for loose faults, and the accuracy rate was 85.6%, the recall rate was 84.8%, and the F1 score was 85.2. Compared with the traditional threshold-based judgment method, the detection accuracy of this system in all fault types is improved, especially in the detection of complex fault types (such as loose faults and electrical faults), the performance advantage of the system is more obvious.





3.3 Analysis of Results

By introducing DQN algorithm and multi-sensor data fusion technology, the detection accuracy of the system in complex environments is significantly improved. By learning the mapping relationship between the claw state and the maintenance decision, the DQN algorithm can automatically generate the optimal maintenance strategy, reducing the possibility of human intervention and misjudgment. Multi-sensor data fusion technology improves the system's ability to detect complex faults by comprehensively using data from different sensors. At the same time, the application of Internet of Things technology makes data collection and transmission more efficient, providing reliable support for real-time decision-making.

In addition, the experimental results also show that the performance of the system has a certain dependence on the quality and quantity of sensor data. When the data is sufficient and the quality is high, the detection accuracy and decision-making reliability of the system are higher. Therefore, future research can further optimize sensor layout and data acquisition strategies to improve the overall performance of the system.

4 Discussion

4.1 System Advantages

Real-time:Real-time data collection and transmission are realized through the Internet of Things technology to ensure that the system can quickly respond to changes in the claw state and meet the high requirements for real-time performance in industrial production.

Intelligent: Using deep reinforcement learning algorithms, the system can learn and optimize maintenance decisions autonomously, reducing manual intervention and improving the automation level of the system.

Multi-sensor fusion: By fusing multi-sensor data, the system can more comprehensively evaluate the state of the gripper and improve the detection accuracy. The application of this technology not only improves the reliability of the system, but also provides stronger support for the diagnosis of complex faults.

Scalability: The system architecture is designed with good scalability, and the sensor type and number can be flexibly adjusted according to different industrial scenarios and needs to further optimize the system performance.

4.2 System limitations

Data dependency: The performance of the system depends on high-quality training data, and insufficient data can lead to model overfitting. In practical applications, it is necessary to ensure the diversity and integrity of data to improve the generalization ability of the model.

Computing resource requirements: The training of deep reinforcement learning algorithms requires high computing resources, which may limit the deployment scope of the system. Future research can explore more efficient algorithm optimization strategies to reduce the demand for computing resources.

Adaptability to complex environments: Although the system performs well in an experimental environment, it may face more complex operating conditions and interference factors in a real-world industrial environment. Therefore, the robustness and adaptability of the system still need to be further verified and optimized.

4.3 Future Improvement Directions

Dataset expansion: Increase the size of the dataset and improve the generalization ability of the model. Future studies could consider introducing more fault types and operating condition data to further optimize the performance of the system.

Algorithm optimization: Try more advanced reinforcement learning algorithms (such as PPO and A3C) to further improve system performance. In addition, multi-agent reinforcement learning algorithms can be explored for more efficient collaborative decision-making.

Real-world deployment validation: Deploy the system in a real-world industrial environment to verify its performance in real-world applications. By comparing it with traditional maintenance methods, the superiority and practicability of the system are further demonstrated.

System integration: Integrate the system with other intelligent manufacturing systems, such as production scheduling systems and quality inspection systems, to achieve more efficient production process optimization and collaborative management.

5 Conclusion

In this study, a claw replacement and maintenance system for industrial robots based on the Internet of Things and deep reinforcement learning was proposed, which realized real-time monitoring and intelligent maintenance decision-making by integrating Deep Q Network (DQN) and multi-sensor data fusion technology. The experimental results show that the average accuracy of the system in the claw state recognition and maintenance decision-making reaches 86.2%, which is significantly improved compared with the traditional method, and provides reliable technical support for the efficient operation of the intelligent manufacturing system. Future research will further optimize system performance, scale datasets, experiment with more advanced algorithms, and validate and apply them in real-world industrial environments. Through continuous improvement and optimization, the system is expected to be widely used in the field of intelligent manufacturing, providing strong support for the intelligence and efficiency of industrial production.

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