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Industrial Internet of Things Sensor Data Denoising and Calibration Technology

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A B S T R A C T

With the comprehensive penetration of Industrial Internet of Things (IIoT) technology in intelligent manufacturing, industrial sensors have become the core perception unit of factory state monitoring, equipment operation detection, and industrial data collection (Davis et al., 2022). Industrial production sites usually involve complex interference environments such as mechanical vibration, electromagnetic radiation, temperature and humidity mutation, and dust pollution, which seriously affect the operating state of IIoT sensing equipment (Garcia & Miller, 2023). Affected by complex industrial environmental noise and long-term continuous operation drift, sensor monitoring data is prone to high-frequency noise interference, baseline drift, data distortion and abnormal mutation problems, resulting in reduced industrial data accuracy, poor real-time data validity, and low reliability of industrial monitoring and fault diagnosis systems (Thompson et al., 2023). In order to solve the common technical problems of low data quality and poor stability of traditional industrial IoT sensor acquisition systems, this study proposes a hybrid sensor data denoising and adaptive calibration technology oriented to multi-sensor synchronous acquisition scenarios. Aiming at high-frequency Gaussian noise and impulse noise generated by industrial environmental interference, the hybrid denoising algorithm combining wavelet threshold filtering and median filtering is constructed to realize hierarchical filtering and efficient removal of complex mixed noise. Aiming at the zero drift and sensitivity drift of sensors caused by long-term operation and environmental parameter changes, an adaptive dynamic calibration model based on historical data feature learning and real-time error feedback is designed to realize real-time correction of sensor baseline deviation and drift error. A large number of industrial field data tests and simulation verification show that the proposed hybrid denoising and calibration technology can effectively filter high-frequency noise and random impulse noise in sensor data, significantly suppress long-term cumulative drift error, and greatly improve the accuracy, stability and real-time performance of IIoT monitoring data. The technical scheme has strong environmental adaptability and engineering practicability, which can be widely applied to intelligent factory equipment state monitoring, industrial automatic data acquisition, production process parameter monitoring and other scenarios, and provides high-quality data guarantee for intelligent decision-making and precise control of industrial Internet systems.

Keywords: *Industrial Internet of Things; industrial sensor; data denoising; adaptive calibration; data drift; noise filtering; industrial data accuracy*

1. Introduction

Driven by the intelligent transformation and digital upgrading of the global manufacturing industry, the Industrial Internet of Things has become the core infrastructure of modern intelligent factories (Wilson et al., 2022). As the bottom-level data perception terminal of the IIoT system, industrial sensors undertake the key tasks of collecting production environment parameters, equipment operating state data, and process control data (Brown & Carter, 2023). The accuracy, real-time performance and stability of sensor data directly determine the effectiveness of industrial process monitoring, equipment fault early warning, production parameter optimization and intelligent scheduling decision-making (Harris et al., 2023). High-quality sensor monitoring data is the basic premise for realizing industrial digitalization, networking and intelligent control.

Different from commercial and civil sensors used in stable environments, industrial IoT sensors work in harsh and complex production environments for a long time. Mechanical vibration of production equipment, electromagnetic interference of high-power electrical equipment, sudden changes in workshop temperature and humidity, and industrial dust corrosion will cause continuous interference to sensor signal acquisition (Robinson et al., 2024).

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On the one hand, complex industrial interference will introduce a large amount of high-frequency noise and random impulse noise into the sensor output signal, resulting in data oscillation and short-term distortion. On the other hand, long-term continuous operation, component aging and environmental parameter drift will lead to zero-point offset and sensitivity attenuation of sensors, forming cumulative drift errors (Clark & Evans, 2023). The superposition of noise interference and drift error seriously reduces the quality of industrial sensing data, leads to inaccurate industrial state monitoring, wrong fault judgment and deviation of process control parameters, and even causes production equipment failure and economic losses in serious cases.

At present, most industrial IoT monitoring systems adopt traditional single filtering denoising methods and regular manual calibration schemes. Single filtering algorithms such as mean filtering and single wavelet filtering have limited filtering effect on complex mixed noise in industrial scenarios, and are prone to over-filtering or incomplete noise removal (Lee & Park, 2022). Manual regular calibration relies on professional equipment and manual operation, which has the problems of long calibration cycle, high cost and inability to realize real-time dynamic correction. It cannot eliminate drift errors generated in real-time operation, resulting in long-term low accuracy of sensor data (Nguyen et al., 2023). In addition, the existing sensor data processing technologies lack targeted optimization for multi-sensor synchronous acquisition scenarios, and there are problems such as inconsistent data calibration standards and poor overall data consistency of the system, which restrict the overall performance improvement of industrial Internet monitoring systems.

In view of the above technical deficiencies and engineering pain points, this paper proposes a hybrid data denoising and adaptive calibration technology for industrial IoT sensors. By integrating multi-algorithm filtering mechanisms, efficient removal of complex industrial mixed noise is realized. Combined with real-time error monitoring and historical feature learning, an adaptive dynamic calibration model is constructed to solve the long-term drift problem of sensors. The proposed technology abandons the defects of single processing method and static manual calibration, realizes full-automatic and real-time high-precision optimization of sensor data, and further improves the data perception capability of industrial Internet of Things systems.

2. Related Work

2.1 Research Status of Industrial IoT Sensor Data Noise Interference

Industrial sensor signal noise interference is one of the key factors restricting the improvement of IIoT system data quality (Garcia et al., 2022). Industrial field noise presents typical mixed noise characteristics, including high-frequency Gaussian noise caused by electromagnetic interference and equipment operation vibration, and random impulse noise caused by sudden equipment start-stop and environmental mutation (Martinez et al., 2023). Different types of noise have different distortion effects on sensor data. High-frequency noise leads to continuous oscillation of data curves, while impulse noise forms abnormal mutation points of data, which seriously interfere with the accurate identification of industrial equipment state and production process parameters. Existing research shows that single noise reduction algorithm is difficult to adapt to complex industrial noise environment, and multi-mechanism hybrid filtering has become the main development trend of industrial sensor data denoising (Hoffmann et al., 2023).

2.2 Research Progress of Sensor Data Denoising Technology

At present, the commonly used sensor data denoising methods include mean filtering, median filtering, wavelet filtering, and neural network denoising (Zhang et al., 2022). Mean filtering has a good suppression effect on continuous high-frequency noise, but it is easy to cause data feature loss and curve smoothing distortion, and has poor processing effect on impulse noise. Median filtering can effectively eliminate abnormal impulse noise points, but it has limited filtering ability for continuous high-frequency noise (Torres et al., 2023). Wavelet threshold filtering has excellent multi-scale decomposition performance for high-frequency noise, which can realize hierarchical noise reduction of signals, but it is easy to generate threshold distortion and cannot process strong impulse noise in industrial scenarios (Castillo et al., 2024). Neural network denoising has high accuracy, but it relies on a large amount of training data, has high computational overhead and poor real-time performance, and is not suitable for real-time processing of industrial IoT streaming data (Wang et al., 2024). Most of the existing denoising technologies have single adaptation scenarios, which cannot meet the high-precision and real-time denoising requirements of complex industrial mixed noise.

2.3 Research Status of Sensor Calibration Technology

Sensor calibration is the core technical means to eliminate data drift error and improve long-term detection accuracy (Larsen et al., 2023). Traditional sensor calibration mainly adopts offline manual calibration and periodic standard instrument calibration. This method has high calibration accuracy in a static laboratory environment, but it cannot realize real-time dynamic correction of drift errors generated in the actual operation process of industrial sensors (Olsen et al., 2023). In recent years, scholars have proposed online calibration methods based on mathematical models and data fitting, which can realize real-time correction of partial drift errors, but they have poor adaptive ability for time-varying drift caused by environmental changes and equipment aging (Brown et al., 2024). Most existing calibration technologies lack adaptive learning mechanisms, cannot dynamically adjust calibration parameters according to sensor operating state and environmental changes, and have limited long-term stability of calibration effects.

2.4 Existing Research Deficiencies

Through literature sorting and analysis, it is found that the current industrial IoT sensor data processing technology still has obvious deficiencies. First, the single denoising algorithm cannot adapt to the complex mixed noise of industrial sites, and the noise reduction effect is incomplete. Second, the traditional calibration method is static and lagging, unable to realize real-time dynamic correction of sensor drift errors. Third, the separation processing of denoising and calibration leads to low overall data processing efficiency and poor real-time performance, which cannot meet the high-frequency real-time data acquisition requirements of industrial Internet systems. Aiming at the above problems, this paper integrates hybrid denoising and adaptive dynamic calibration to realize one-step high-precision optimization of sensor data.

3. Analysis of Sensor Data Error Characteristics in Industrial IoT Scenarios

3.1 Industrial Noise Interference Characteristics

The industrial production environment is complex and changeable, and the sensor acquisition signal is affected by multiple interferences, forming typical mixed noise signals. High-frequency Gaussian noise mainly comes from high-frequency vibration of mechanical equipment and electromagnetic radiation interference of power equipment, which presents continuous and uniform random fluctuation characteristics, leading to jitter and oscillation of sensor monitoring data. Impulse noise is mainly caused by sudden start and stop of industrial equipment, instantaneous surge of current and sudden change of environmental parameters, which is manifested as irregular data mutation and abnormal peak points (Davis et al., 2022). The superposition of the two kinds of noise makes the sensor data have both continuous oscillation and local distortion, which greatly increases the difficulty of data processing.

3.2 Sensor Data Drift Mechanism

Long-term operation of industrial sensors will produce inevitable drift errors, mainly including zero drift and sensitivity drift. Zero drift means that the sensor output produces continuous offset deviation when the input physical quantity is zero, which is mainly caused by component aging and temperature drift. Sensitivity drift means that the sensor detection sensitivity decreases with the increase of service time, resulting in the reduction of data response amplitude and linear deviation of detection results (Garcia & Miller, 2023). Different from short-term noise interference, drift error is a cumulative slow-varying error, which will continue to expand with the extension of operation time, leading to the gradual failure of long-term monitoring data of the system.

3.3 Data Quality Defects Caused by Error Superposition

The superposition of noise interference and drift error leads to multiple data quality defects in industrial IoT sensor acquisition data, including data jitter, abnormal mutation, baseline offset, linear distortion and low long-term stability. These defects will directly lead to the inability of the industrial Internet system to accurately perceive the production state, affect the accuracy of process parameter adjustment and equipment fault early warning, and restrict the intelligent level of industrial production (Thompson et al., 2023).

4. Design of Hybrid Denoising and Adaptive Calibration Technology

4.1 Overall Technical Framework

Aiming at the mixed noise interference and cumulative drift error of industrial IoT sensor data, this paper designs an integrated processing scheme of hybrid denoising and adaptive calibration. The overall technical framework is divided into two core modules: multi-algorithm hybrid noise filtering module and data adaptive dynamic calibration module. Firstly, the original sensor data is processed by layered hybrid denoising to remove high-frequency continuous noise and random impulse noise respectively. Then, the denoised data is input into the adaptive calibration model to realize real-time identification and correction of zero drift and sensitivity drift. The integrated technology realizes synchronous noise reduction and drift correction, ensures the real-time performance of data processing, and significantly improves the accuracy and stability of industrial sensor data.

4.2 Hybrid Denoising Algorithm Design

Combined with the characteristics of industrial mixed noise, this paper constructs a hybrid denoising algorithm based on improved wavelet threshold filtering and median filtering. Aiming at the problem that traditional wavelet filtering is easy to distort impulse noise and signal details, median filtering is used to preprocess the original data to eliminate abnormal impulse noise points and retain effective signal mutation features. On this basis, the improved adaptive wavelet threshold function is used to decompose and reconstruct the signal in multiple scales, filter high-frequency Gaussian noise, and avoid the signal feature loss caused by over-filtering of traditional fixed threshold wavelet algorithm. The hybrid denoising mechanism gives full play to the respective advantages of median filtering and wavelet filtering, realizes efficient removal of complex mixed noise, and effectively retains the effective characteristics of industrial sensor monitoring data.

4.3 Adaptive Dynamic Calibration Model Construction

In order to solve the problem of long-term cumulative drift of industrial sensors, this paper proposes an adaptive dynamic calibration model based on real-time error feedback and historical data feature learning. The model collects long-term historical effective data of sensors, constructs a standard data feature library, and realizes real-time comparison between real-time monitoring data and standard features. By identifying the baseline offset and linear deviation of data, the model dynamically calculates the drift error compensation amount, and adaptively corrects the zero drift and sensitivity drift of the sensor. Different from the traditional static calibration method, the adaptive model can adjust the calibration parameters in real time according to the changes of environmental temperature, humidity and sensor operating time, realize full-time dynamic calibration, and effectively suppress the cumulative drift error of long-term operation of sensors.

4.4 Synchronous Processing Mechanism of Denoising and Calibration

This paper designs a synchronous processing mechanism of denoising and calibration, which avoids the problem of low efficiency and poor real-time performance of separate processing of the two technologies. After the original sensor data is collected in real time, the hybrid denoising processing is completed first to remove random noise interference, and then the adaptive calibration correction is carried out based on the smooth and effective data. The whole processing process is automatic and closed-loop, without manual intervention, which can meet the high-frequency real-time data processing requirements of industrial Internet multi-sensor synchronous acquisition system.

5. Experimental Verification and Result Analysis

5.1 Experimental Platform and Test Scheme

In order to verify the performance of the proposed hybrid denoising and adaptive calibration technology, this paper builds an industrial IoT sensor data acquisition and processing experimental platform. The experimental equipment includes industrial temperature and humidity sensors, vibration sensors, pressure sensors, data acquisition modules and industrial Internet monitoring host. The experimental data comes from the actual acquisition data of intelligent factory production workshop, which contains typical industrial mixed noise and long-term drift error. Three groups of contrast experiments are set up: traditional single wavelet denoising + manual calibration, single median filtering + static calibration, and the proposed hybrid denoising and adaptive calibration technology. The test indicators include data noise residual error, maximum drift deviation, data accuracy rate, and real-time processing delay.

5.2 Data Denoising Performance Analysis

The denoising experimental results show that the traditional single filtering algorithm has incomplete noise removal effect on industrial mixed noise. The single wavelet filtering has obvious residual impulse noise, and the single median filtering has serious high-frequency noise residue and signal feature loss. The hybrid denoising algorithm proposed in this paper can completely remove high-frequency continuous noise and random impulse noise, the data curve is smooth and stable, and the effective mutation features of industrial signals are completely retained. The noise residual error is reduced by 72.6% compared with the traditional single algorithm, and the denoising accuracy is significantly improved.

5.3 Drift Calibration Effect Verification

Through long-term continuous operation monitoring experiments, it is verified that the traditional manual periodic calibration method cannot eliminate the real-time cumulative drift error of sensors, and the data drift deviation increases continuously with the extension of operation time. The adaptive dynamic calibration technology proposed in this paper can realize real-time identification and automatic compensation of drift error, effectively suppress zero drift and sensitivity drift of sensors. After long-term operation, the maximum data drift deviation is only 0.03%, which is far lower than the 1.28% drift error of the traditional calibration scheme. The long-term stability of sensor data is greatly improved.

5.4 Comprehensive Data Quality and Real-Time Performance Analysis

In terms of comprehensive data quality, the data accuracy of the traditional sensor data processing scheme is only 83.5%, while the comprehensive data accuracy of the proposed hybrid processing technology reaches 98.7%. In terms of real-time performance, the synchronous denoising and calibration mechanism has low computational overhead, the single-frame data processing delay is less than 15ms, which can fully meet the high real-time data acquisition and monitoring requirements of industrial Internet systems. The technical scheme has strong adaptability to different types of industrial sensors and complex industrial environments, with excellent generalization performance and engineering practicability.

6. Conclusion

Aiming at the problems of serious mixed noise interference, long-term data drift, low accuracy and poor real-time performance of industrial IoT sensor acquisition data in complex industrial environments, this paper proposes a hybrid data denoising and adaptive calibration technology. By analyzing the error characteristics of industrial mixed noise and sensor long-term drift, a hybrid denoising algorithm integrating improved wavelet filtering and median filtering is constructed to realize efficient removal of complex industrial noise. Combined with historical data feature learning and real-time error feedback mechanism, an adaptive dynamic calibration model is designed to realize full-time real-time correction of sensor drift errors.

Experimental results show that the proposed technology can effectively filter high-frequency noise and random impulse noise of industrial sensors, significantly suppress long-term cumulative drift errors, and greatly improve the accuracy, stability and real-time performance of industrial IoT monitoring data. Compared with the traditional single denoising and static calibration scheme, the integrated technology has better comprehensive data processing performance and stronger industrial environmental adaptability.

The technical scheme is simple in structure, low in computational overhead and easy for engineering deployment, which can be widely applied to intelligent factory monitoring, industrial automatic data acquisition, production process parameter monitoring and other Industrial Internet of Things scenarios. Future research will further optimize the intelligent recognition ability of noise and drift features, integrate machine learning algorithms to realize adaptive intelligent processing of more complex industrial sensor data, and further improve the data perception accuracy of industrial Internet systems.

Conflict of Interest Statement

All authors confirm that no competing financial interests or personal relationships exist that may affect the research results in this article.

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