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Research on Real Time Condition Monitoring and Fault Warning System for Construction Machinery under Multi Source Heterogeneous Data Fusion

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Abstract: This study focuses on the application of multi-source heterogeneous data fusion in real-time status monitoring and fault warning systems for construction machinery, and conducts in-depth analysis of the latest developments in status monitoring and fault diagnosis technology for construction machinery. A monitoring scheme combining data-driven and machine learning is proposed to address the problem of frequent failures in construction machinery in complex operating environments. This solution utilizes efficient data collection and processing from multiple sensors, and applies deep learning models to achieve fault prediction and diagnosis. It can effectively identify potential faults, prevent risks in advance, and improve equipment reliability and operational safety. This article starts with the overall design architecture and core technologies, and provides a detailed introduction to the construction process of data preprocessing, feature extraction, and fault diagnosis models. It also explores the challenges of outdoor operating conditions in monitoring the status of construction machinery. Research has shown that the application of automated state monitoring and early warning systems can significantly reduce the incidence of failures, minimize economic losses, and improve operational efficiency and safety.

1. Introduction

With the rapid development of modern science and technology, engineering machinery and equipment have been widely used in various industrial production fields, and the monitoring and fault diagnosis of equipment operation status have become increasingly important. By monitoring the operation status of the equipment in real-time, it is possible to comprehensively understand the working conditions of the machinery during driving and construction operations, and quickly determine whether it is in a normal state[1]. At the same time, when a fault occurs, the system can accurately locate the fault location, analyze the cause, predict the future development trend of equipment performance, thereby improving the overall safety of mechanical equipment and reducing the risk of sudden failures[2]. If there is an abnormality in the equipment, maintenance personnel can quickly identify the fault condition, take corresponding measures for repair, avoid production stagnation or major accidents, and effectively extend the service life of the equipment. China has been conducting research on the monitoring technology of the operating status of construction machinery and equipment since the 1980s. Nowadays, with the continuous upgrading of technological means, cutting-edge technologies such as laser testing and fiber optic transmission are gradually introduced into the status monitoring of engineering machinery equipment. With their advantages of fast signal transmission speed and large data capacity, efficient information processing has been achieved. In addition, integrating artificial intelligence technology with neural networks and expert systems into the monitoring process can achieve intelligent management of the operating status of engineering machinery equipment[3]. In complex construction environments, the distribution of construction machinery and equipment is usually scattered, and timely grasp of vehicle operation status, location information, and fault conditions has become the key to construction management. To address this challenge, a system that can achieve automation and real-time monitoring is needed. With the increasing complexity and diversification of equipment types, traditional regular maintenance methods are no longer sufficient to meet the demand, and data-driven state monitoring and fault diagnosis technologies have emerged[4]. This article will focus on exploring the latest developments in engineering machinery condition monitoring technology, and propose a monitoring system that integrates data acquisition, preprocessing, and advanced machine learning models. The application prospects of this system in improving equipment operating efficiency and reducing failure rates will be analyzed in depth, providing theoretical support and practical reference for future research and application of engineering machinery equipment condition monitoring and fault diagnosis technology.

2. Related technologies for monitoring the operating status of construction machinery

The operation status monitoring technology of construction machinery equipment is a technology that collects various signals of the equipment in working or stationary state through sensors, processes and analyzes these signals, and combines them with historical data of the equipment to obtain real-time operation status of the equipment and its components in a specific order. This technology can predict the changing trend of equipment faults and quickly locate the location of faults. The early state monitoring methods in China mainly included vibration monitoring, oil sample analysis, temperature measurement, and ultrasonic testing, among which vibration monitoring was the most commonly used core means. The development of status monitoring technology for construction machinery in China can be divided into two main stages: the first stage is based on sensor signal acquisition and processing technology, using principles such as light sensitivity, heat sensitivity, Hall effect, and electromagnetic induction to obtain various parameters of equipment operation status, and transmitting these data to microcomputers for comparison and analysis with historical data stored in databases to determine the health status of equipment. The second stage is based on intelligent diagnostic technology using artificial intelligence and expert systems, relying on computer simulations of human reasoning and decision-making processes to achieve intelligent fault diagnosis. This technology has gradually replaced traditional sensor monitoring methods and become the mainstream application technology for status monitoring of construction machinery equipment, playing an important role in improving the accuracy and efficiency of fault diagnosis.

2.1. Network based remote monitoring technology

Installing sensors on construction machinery can effectively obtain various dynamic parameter signals of the equipment in both operating and stationary states. To ensure that these signals correspond one-to-one with the corresponding mechanical equipment, engineers will assign a number to each device. The combination of monitoring technology and computer networks utilizes wireless communication technology to transmit real-time data collected by sensors to computer systems, thereby achieving remote monitoring of construction machinery. This method enables real-time analysis of the operating status of large construction vehicles, providing timely technical support and maintenance support for equipment. Sensors send signals to the computer server in the monitoring center through GPRS wireless network, which uses a professional operating system to perform time-domain and frequency-domain analysis on dynamic signals and applies the results to equipment status monitoring. During the time-domain analysis process, operational noise may interfere with the data, making it difficult for personnel to accurately determine the equipment status. Usually, if there are periodic pulse peaks in the vibration signal, it may indicate that a component is damaged. By converting time-domain signals into frequency-domain signals, the vibration amplitude of equipment can be evaluated based on frequency distribution. The staff will compare these frequencies with the normal spectrum to identify potential types of faults. The computer server in the monitoring center will promptly transmit fault information to on-site operators, helping them quickly locate problems and carry out repairs, thereby ensuring the continuous normal operation of mechanical equipment.

2.2. Neural Network Diagnostic Technology

Artificial neural networks are increasingly playing a critical role in state monitoring and fault diagnosis of construction machinery. This type of network mimics the complex structure of the human nervous system, consisting of numerous simple neural units interconnected and combined with fuzzy control for inference. Its significant functions include fault tolerance, reasoning, memory, adaptability, self-learning, and processing of complex patterns. In the field of intelligent monitoring, there are three relatively mature neural network applications: one is a network used for predicting operating conditions, the other is a network for fault pattern recognition, and the third is an intelligent diagnostic system based on neural networks. The state prediction network has improved the early recognition ability of fault diagnosis and enhanced the response speed of intelligent monitoring systems; The fault mode recognition network has high fault tolerance and can determine the true fault situation of the equipment through the diverse state information monitored.

Researchers have used BP neural networks to diagnose diesel engine faults, selecting logarithmic functions (logsig) as the activation function for hidden layer neurons, while using pure linear functions (purelin) as the transfer function for the output layer. Input the collected raw fault samples into the neural network and write the corresponding program using MATLAB software. When the minimum mean square error reaches 1×10^{-8}, the training will end. Finally, by establishing a network mapping relationship and calculating the fault sample data to be tested, the cause of the diesel engine fault is determined, thereby further verifying the effectiveness and feasibility of neural networks in engineering machinery state monitoring and fault diagnosis. Overall, as a cutting-edge diagnostic method, neural network technology does not require tedious data organization, reducing labor costs. In addition, the training of artificial neural networks mainly focuses on specific instances, thus avoiding the interference of external factors. Although this technology has many advantages, such as not needing to organize and summarize expert knowledge to obtain network knowledge, there are still some limitations, mainly manifested in the failure to fully utilize expert experience, relatively weak logic, and lack of sufficient persuasiveness in the monitoring process.

2.3. Data preprocessing methods

In construction machinery, various types of sensors are used, including accelerometers, temperature sensors, and pressure sensors. These devices can obtain real-time key parameters of machinery during operation, such as vibration, temperature, and pressure, which are crucial for evaluating the operational status and health level of the machinery. In the process of data collection, it is necessary to pay attention to multiple factors such as sampling frequency, resolution, and data processing methods. When selecting the sampling frequency, a balance needs to be struck between energy consumption and information loss. Typically, data is transmitted through machines at thousands of Hertz.

The signal received from the vibration sensor is usually a time series that can be analyzed at different frequencies using mathematical tools such as the Fourier transform. In order to capture spectral properties, such as spectral frequencies and spectral fields, we will investigate the functions of the machine. The temperature center of the measured variable is also the measured temperature. We can determine the temperature by measuring the temperature.

2.4. Feature extraction technology

Performance plays a key role in observing the state of the machine. Key information that can effectively reflect the state of the machine is extracted from the raw data. This process simplifies complex data into easy-to-understand and unique properties, often collected through vibration templates. An important example is the square root (RMS), where vibration plays a decisive role. RMS provides a wealth of signal energy insight, which gives us valuable insights into the mechanical state. Using certain techniques, such as Fourier transform, it is possible to convert the time signal into a frequency range. What is a spectrometer? The energy density of the spectrum is critical. This helps us understand how vibrations are distributed across different frequencies and detect unusual vibrations at specific frequencies. Robot events improve the selection of personalities, thus making them more effective and representative. For example, search techniques have shown that primary temporal analysis (PKA) processes raw data in a linear manner, independent of major component transformations, and that it can effectively reduce attributes while storing as much information as possible.

3. Model building

The machine learns to process large amounts of data from a series of sensors within the model framework to accurately detect errors. A common approach is to learn how to monitor: model, categorize market data or forecast data. In system diagnostics, for example, support vector (SVM) or random forest models are used. These models are learned by correlating the sensor's vibration data with the corresponding fault markers, which allow for a relationship between vibration and Gurkat. ig neural networks (CNNS) and receiver networks (RNNS) have a large amount of valuable sensor data. They automatically detect complex functions and detect all kinds of interference. Applications, the use of machines, it is not limited to vibrators; It also contains measurements such as temperature and pressure. This function effectively monitors temperature fluctuations and helps prevent possible interference. Deep learning enables the merging of abstract attributes and the recognition of complex patterns collected by sensors, thus enabling effective fault diagnosis. For example, CNNS are becoming increasingly modern, and by building layers of multiple thicknesses and gradients, models can learn information from a variety of systems, allowing them to extract errors from vibrations. Neural network rewriting (RNN) is used for time series. The instance mode was assigned to analyze the vibration pattern of the r-53 over time, learn the signal pattern, and identify possible faults. As an example of an example, the following formula:

$$h_t = f(W_{hx}x_t + W_{hh}x_{t-1} + b_h) \tag{1}$$

$$y_t = g(W_{yh}h_t + b_y) \tag{2}$$

Rather than just a unified framework for building deep learning, we can leverage different types of deep research, where CNNS and reactive neural networks (NNS) have developed a structure called RNN-CNN. A method that utilizes the advantages of the two models, thus improving the accuracy and reliability of fault diagnosis.

Real-time fault diagnosis systems must be able to react quickly to data collected by sensors. Detect and predict defects in a timely manner and take measures to prevent equipment failure if necessary. When creating D, attention should be paid to the availability and validity of the data. Vibrations, such as frequencies, reach thousands of Hertz. Processing this data requires efficient algorithms and system structures, so that we can process a lot of information. This is an important step in ensuring data stability in real time.

4. Experiment and result analysis

During the authentication phase, the error and error monitoring system ensures reliability and stability. To evaluate performance values under real data conditions and to identify errors. Typically, the data collected is in training - and testing subjects. Most of the data is used for training and processing model parameters, and others are used to test the performance of the model. We can use 70% of the data to measure the validity of the model, and the rest less than 30%.

For example, during model testing, vibration data is needed to identify various defects. But first the inventory, then the wheels and the motor. The model must be able to accurately classify and identify errors. To evaluate efficiency, we can use multiple metrics. Like a bad matrix, accuracy, history and formula. The confusion matrix shows the predictive performance of the model in different categories, including the number of true suspected cases, true and false negatives. The correct proportion of the sample is reflected in this accuracy, and if the model predicts correctly, the positive cases are identified when Recal assesses his ability. This applies especially to misdiagnosis, when weight falls on remnants, which can effectively reduce the risk of undiagnosed cases. In addition, with precision and tunability, Formula 1 scores can be tailored to model results across all categories. In operational observation and fault diagnosis, effect evaluation and analysis are key steps to verify the reliability of the model and the reliability of the results. When we perform a comprehensive evaluation of the model's performance against real data, we get a better picture of its merits. Disadvantages and scope of application. Thus, for example, the diagnostic model obtained 90% accuracy through vibration data in the test group, 85 percent recall and 0.88 cents F-1. These indicators objectively reflect the model's ability to identify and classify error types.

Table 1: Evaluation results of fault diagnosis model

index	Fault diagnosis model results
Accuracy	0.92
Recall rate	0.88
F1-score	0.9
Fault prediction lead time	7 days

In addition, in addition to traditional evaluation indicators, attention should also be paid to the effectiveness of the model in practical applications. For example, the lead time of fault prediction is a key indicator. If the model can successfully predict and issue warnings one week before the fault occurs, achieving a 7-day lead time, then the application value of this model in actual production is significant. At the same time, evaluating the robustness of the model is also very important, including its performance under different environmental conditions and its ability to handle small sample or imbalanced datasets, which are core factors in measuring the reliability of the model. The specific evaluation results of the fault diagnosis model are detailed in Table 1.

5. Conclusion

The continuous progress and application of engineering machinery condition monitoring and fault diagnosis technology are bringing profound changes to the modern industrial field. This article will delve into key aspects such as sensor data acquisition, feature extraction, establishment and experimental verification of machine learning and deep learning models, comprehensively showcasing important technologies and methods in this field. With the continuous improvement of intelligence and automation level of construction machinery, condition monitoring and fault diagnosis have become key means to ensure stable operation of equipment and improve production efficiency.

However, we must also be aware of the challenges faced in technological development, such as data quality and model generalization ability, which require us to continuously innovate and optimize. We look forward to continuous efforts and exploration in the field of construction machinery, which can provide more reliable and intelligent solutions for industrial production.

References

[1] Zhou H, Huang X, Wen G, et al. Construction of health indicators for condition monitoring of rotating machinery: A review of the research[J].Expert Systems with Application, 2022.

[2] Olcese Umberto. Equipment Detection and Maintenance in Mechanical Workshop Based on Anomaly Detection Algorithm[J]. Kinetic Mechanical Engineering, 2022, 3(2): 1-9.

[3] Huang L, Pan X, Liu Y G L .An Unsupervised Machine Learning Approach for Monitoring Data Fusion and Health Indicator Construction[J].sensors, 2023, 23(16).

[4] Liu Y, Liu J, Zhang F, et al. Data-model Interactive Health Condition Assessment for Hydropower Unit[J].IOP Publishing Ltd, 2024.DOI:10.1088/1742-6596/2752/1/012020.