Design and Application of an Edge Computing-Based Condition Monitoring and Fault Diagnosis System for Coal Mining Machinery

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Abstract: Addressing the challenges of poor real-time data processing and high bandwidth consumption inherent in traditional cloud computing for coal mining machinery condition monitoring, alongside the limited generalization capability of existing fault diagnosis models, this paper proposes a distributed intelligent monitoring and diagnostic framework integrating edge computing, wireless sensor networks (WSN), and deep learning-based transfer learning techniques. Initially, a multi-source data acquisition system grounded on WSN is established, utilizing the STM32F405 microcontroller, ADXL1005 MEMS sensor, and nRF24L01+ modules to enable high-precision vibration data collection and robust transmission. Subsequently, an edge computing terminal powered by the RK3588 processor is designed, featuring heterogeneous communication and multi-source data aggregation capabilities, effectively reducing data transmission latency. Finally, the fault diagnosis model is refined through transfer learning to filter effective deep features and minimize distribution discrepancies between source and target domains. Experimental results demonstrate that the system achieves 16-bit data acquisition precision, wireless transmission success rates exceeding 98%, and a 12.3% improvement in fault diagnosis accuracy compared to conventional deep learning methods, thereby fulfilling the real-time monitoring and fault diagnosis requirements of equipment operating in the complex environments of coal mines.

Keywords: Edge Computing; Coal Mining Machinery; Fault Diagnosis; Wireless Sensor Network (WSN); RK3588 Processor; Transfer Learning

1. Introduction

The rapid advancement of Internet of Things (IoT) technology is propelling the coal mining industry towards intelligent monitoring paradigms. Critical components of coal mining machinery, such as the bearings in scraper conveyors and hydraulic supports, necessitate real-time surveillance to avert unexpected failures and operational downtime [1,2]. Contemporary mainstream online monitoring systems predominantly rely on traditional cloud computing architectures, wherein data storage, analysis, and fault diagnosis are centralized within cloud hubs. While this approach offers the advantage of low variable costs, its computational capacity often falters under the deluge of vibration data, and extensive transmission distances further undermine real-time responsiveness [3].

Edge computing, as an extension of cloud computing, shifts data processing tasks closer to the network periphery, significantly curtailing bandwidth consumption and transmission latency. When synergized with cloud infrastructure, it substantially enhances data processing immediacy [4]. Current fault diagnosis frameworks based on deep learning and transfer learning leverage convolutional neural networks and autoencoders to extract fault features, addressing challenges such as limited sample availability through model transfer. However, two principal limitations persist: firstly, the absence of selective filtering for deep features permits redundant and noisy information to degrade diagnostic accuracy; secondly, insufficient quantification of distribution discrepancies between source and target domains impairs the model's generalization capability [5].

Wireless Sensor Networks (WSN), as the pivotal perception layer in IoT architectures, comprise nodes integrating sensors, processors, wireless communication, and power modules. Nonetheless, existing WSN nodes employed in coal mining applications suffer from low sampling frequencies, high terminal power consumption, and inadequate wireless transmission rates (below 1 Mbps) [6-8]. In response, this study designs a distributed multi-source data acquisition system paired with an RK3588-based edge computing terminal, in concert with an optimized transfer learning model, to address the critical technical challenges in monitoring and diagnosing coal mining machinery.

2. System Overall Design

2.1 Comprehensive System Architecture

The distributed multi-source data acquisition system predicated upon wireless sensor networks (WSN) typically comprises terminal sensor nodes, aggregation nodes or gateway nodes, a host computer, and corresponding supporting software systems. Their interconnections are depicted in Figure 1.

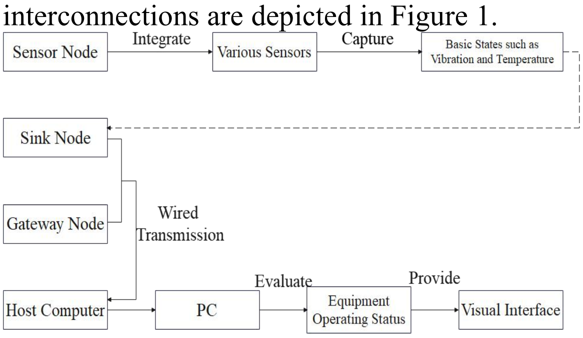

Figure 1. System Structural Relationship

2.2 Terminal Node Design

Deployed on-site, terminal sensor nodes interface with data aggregators and are tasked with capturing a multitude of environmental parameters including temperature, humidity, pressure, and illumination. These nodes are endowed with capabilities for preliminary local processing and analysis of the acquired data—such as data compression, filtering, and aggregation—thereby mitigating the volume of data necessitating transmission and enhancing the efficiency of network resource utilization.

2.3 Aggregation Node Design

Aggregation nodes consolidate data harvested from multiple adjacent sensor nodes, effectively diminishing data transmission traffic and elevating network efficiency. They further execute preprocessing tasks such as compression and data filtering to exclude superfluous information, thus optimizing transmission bandwidth. Additionally, aggregation nodes manage data forwarding and routing responsibilities, ensuring that sensor-derived information traverses the optimal paths to its intended destinations, thereby guaranteeing the reliability and stability of data delivery.

2.4 Host Computer Design

The host computer engages in wireless communication with sensor nodes to facilitate bi-directional data exchange. It collects data relayed from the sensor nodes and archives it either locally or within remote databases. The host system possesses capabilities for real-time data storage, compression, and encryption. Moreover, it performs a gamut of data processing and analytical operations, including filtering, noise reduction, aggregation, and predictive modeling, thereby enabling sophisticated interpretation and utilization of the sensor data.

3. System Hardware Design

The distributed multi-source data acquisition system based on wireless sensor networks proposed in this paper mainly consists of terminal nodes and aggregation nodes.

Regarding the selection of terminal nodes, a dual-core processor architecture is often emblematic, wherein one core is dedicated to vibration data acquisition and high-throughput storage, while the other core manages the wireless communication subsystem responsible for the stable and reliable transmission of data and commands. In this study, however, the terminal node is architected around a single-core processor and is principally composed of a vibration data acquisition module, a high-speed storage module, a 2.4 GHz RF wireless communication module, a power supply module, and a microcontroller unit. Concerning the aggregation nodes, recognizing their imperative role in executing computationally intensive deep learning algorithms for fault diagnosis of coal mining machinery, the system adopts aggregation nodes endowed with robust floating-point and matrix operation capabilities, alongside high flexibility and programmability. Consequently, the aggregation node within the proposed data acquisition system predominantly consists of a high-performance single-board computer, supplemented by power modules, wireless communication interfaces, and storage components.

3.1 Microcontroller Module

The microcontroller module serves as the pivotal core of the wireless sensor network terminal node, orchestrating critical tasks such as data acquisition, wireless communication protocols, and data flow management. The performance of the microcontroller fundamentally dictates the node's processing capacity, instruction execution speed, and real-time responsiveness. A rich set of I/O and peripheral interfaces, along with a high operating clock frequency, facilitates seamless integration with diverse peripheral modules. Tailored for the pragmatic demands of fault diagnosis in coal mining machinery, this study opts for the STM32F405RGT6 microcontroller, which is founded upon the high-performance 32-bit Cortex-M4 RISC core.

3.2 2.4 GHz Wireless Communication Module

In this system architecture, the radio frequency transceiver employs the ultra-low-power nRF24L01+ module, with multiple such modules interconnected to form a star-topology network. The nRF24L01+ features a hardware SPI digital interface supporting speeds up to 10 Mbps and utilizes efficient Gaussian Frequency-Shift Keying (GFSK) modulation, conferring strong anti-interference capabilities. It supports the enhanced ShockBurs t^{TM} transmission mode and has found widespread application in wireless access control, security systems, remote controls, joystick surveying, and industrial sensors, thereby meeting most of the system's requirements outlined above.

3.3 Vibration Data Acquisition Module

The vibrational signals emanating from coal mining machinery predominantly reside within a frequency range of 10 Hz to 20 Hz, necessitating a data acquisition module with a sufficiently high sampling rate to adhere to digital signal processing standards and ensure integrity of vibration information throughout sampling. The proposed vibration data acquisition module comprises two essential components: a MEMS accelerometer and an analog-to-digital converter. The selected accelerometer is the ADXL1005—a low-noise, wide-bandwidth MEMS sensor—which offers a full-scale range of ±100g, a flat frequency response spanning 0 to 24 kHz, and linearity within ±0.25% of full scale. Operated under a 5V power supply, it delivers a sensitivity of 20 mV/g while consuming as little as 1.0 mA. The acquired vibration data is digitized by the ADC, which facilitates streamlined computer-based processing and analysis, thereby enabling the extraction of more precise vibrational feature information.

3.4 Single-Board Computer Platform

A single-board computer (SBC) platform integrates a processor, memory, storage, and other fundamental components into a compact, self-contained computing unit. Driven by the rapid advancements in the Internet of Things (IoT), embedded systems, and artificial intelligence, the application scope of SBCs continues to expand exponentially. For this data acquisition system, the Raspberry Pi 4B is selected owing to its credit-card-sized form factor and comprehensive computational capabilities akin to those found in standard computers. The Raspberry Pi 4B is powered by a 1.5 GHz quad-core ARM Cortex-A72 processor and offers multiple LPDDR4 memory configurations (1 GB, 2 GB, or 4 GB), representing a significant performance enhancement over its predecessors. Despite its elevated performance, the power consumption remains modest—typically between 3 and 5 watts—rendering it well-suited for long-duration deployments or battery-powered scenarios [9,10]. Furthermore, its affordable price point makes it an appealing choice across diverse domains. Figure 2 exhibits the physical appearance of the Raspberry Pi 4B single-board computer.

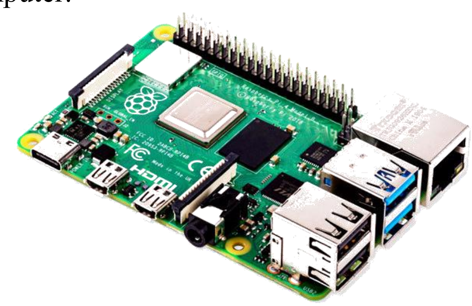

Figure 2. Raspberry Pi 4B Single-Board Computer

4. Edge Computing Terminal and Fault

Diagnosis Model Design

4.1 RK3588 Edge Terminal Hardware

The terminal is architected around the RK3588 processor, fabricated using an 8nm process and equipped with an octa-core CPU configuration comprising four Cortex-A76 and four Cortex-A55 cores, alongside a neural processing unit (NPU) delivering 6 tera operations per second (TOPS). The integrated system comprises: ① a heterogeneous communication module supporting Wi-Fi 6, Ethernet, and LoRa protocols, enabling the aggregation of multi-source data; ② a data storage subsystem featuring a 2TB solid-state drive (SSD) and a 4TB hard disk drive (HDD), employing RAID 2 technology to ensure data redundancy and backup; ③ a power management module with a wide input voltage range from 9 to 36 volts, specifically engineered to accommodate the power supply conditions prevalent in underground coal mining environments.

4.2 Transfer Learning Model Optimization

Building upon a CNN-autoencoder foundational model, the optimization process encompasses the following stages: ①employing wavelet packet transform for the time-frequency analysis of vibration signals, thereby constructing the initial feature set [2]; ② extracting deep features through the autoencoder, followed by utilization of the Relief-F algorithm to filter effective features, effectively eliminating approximately 35% of redundant attributes; ③ transferring the model parameters from the source domain—laboratory-simulated fault samples—to the target domain represented by in-situ coal mine samples, wherein cosine distance is employed to quantify distributional discrepancies between source and target domains, and the fine-tuning learning rate is adaptively modulated within the range of 0.001 to 0.01; ④ integrating a Softmax classifier to output precise fault classifications, including but not limited to bearing inner ring faults and outer ring faults.

5. Experimental Evaluation

5.1 Data Acquisition Performance Assessment

Within the context of monitoring bearings on a coal mine scraper conveyor—under environmental conditions spanning from - 10℃ to 45℃ and subjected to electromagnetic interference intensities up to 80 dBμV/m—the system's performance metrics are as follows:

Sampling Accuracy: The AD7606-4's 16-bit resolution ensures vibration signal measurement errors are constrained within 0.5%, while the ADXL1005 achieves a 100% capture rate for vibration signals in the frequency band of 10 to 20 Hz;

Wireless Transmission: Employing the nRF24L01+ in a star network topology, data transmission success rates reach 98.7% over a 50-meter distance, with an average latency of 18 milliseconds, thereby fulfilling real-time monitoring requirements where latency thresholds remain below 50 milliseconds;

Terminal Power Consumption: The terminal node utilizes an adaptive sleep mode—activating during data acquisition and entering dormant states during idleness—yielding a single-charge operational lifespan of up to six months, effectively doubling the endurance compared to conventional nodes.

5.2 Fault Diagnosis Performance Evaluation

The rolling bearings of a scraper conveyor served as the test subject. Four distinct states were examined: normal operation, inner ring fault, outer ring fault, and rolling element fault. For each condition, 1000 sample sets were collected, comprising 3000 source domain samples and 1000 target domain samples.

Diagnostic Accuracy: The optimized transfer learning model achieved a diagnostic accuracy of 96.8%, representing an improvement of 12.3% over the conventional CNN model (84.5%) and a 6.6% increase compared to the transfer learning model without feature selection (90.2%);

Edge Processing Latency: The inference time per sample on the RK3588 terminal was measured at 23 milliseconds, demonstrating an 84.7% reduction relative to cloud-based processing, which required 150 milliseconds.

6. Conclusion

Addressing the critical challenges in condition monitoring and fault diagnosis of coal mining machinery, this paper presents a distributed data acquisition system based on Wireless Sensor Networks (WSN) alongside an RK3588 edge computing terminal. By integrating an optimized transfer learning model, a comprehensive solution of "precise data acquisition—real-time edge processing—intelligent fault diagnosis" has been realized. The principal conclusions are as follows:

1. The designed terminal node achieves 16-bit acquisition precision, wireless transmission success rates exceeding 98%, and a six-month battery lifespan, thereby fulfilling the multi-source data collection demands within the complex and harsh environment of coal mines;
2. The RK3588 edge terminal realizes inference latency as low as 23 milliseconds, representing an 84.7% reduction compared to cloud-center processing, significantly enhancing the real-time capability of fault diagnosis;
3. The refined transfer learning model attains a diagnostic accuracy of 96.8%, improving upon conventional methods by 12.3%, effectively addressing the generalization challenges posed by limited sample sizes and operational variations.

This system is readily deployable for monitoring coal mining equipment such as scraper conveyors and hydraulic supports, offering robust technological support for the intelligent operation and maintenance of mines. Future enhancements through improved environmental protection and multi-component model expansion promise to further broaden its applicability.

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