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Research on mechanical vibration monitoring based on wireless sensor network and sparse Bayes

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Abstract

Mechanical vibration monitoring for rotating mechanical equipment can improve the safety and reliability of the equipment. The traditional wired monitoring technology faces problems such as high-frequency signal pickup and high-precision data collection. Therefore, this paper proposes optimization techniques for mechanical vibration monitoring and signal processing based on wireless sensor networks. First, the hardware design uses high-performance STM32 as the control center and Si4463 as the wireless transceiver core. The monitoring node uses a high-precision MEMS acceleration sensor with a 16-bit resolution ADC acquisition chip to achieve high-frequency, high-precision acquisition of vibration signals. Then, the bearing vibration signal optimization method is studied, and the sparse Bayes algorithm is proposed as a compressed sensing reconstruction algorithm. Finally, the difference in reconstruction accuracy between this method and the traditional reconstruction algorithm is compared through experiments and the effect of this method on the reconstruction performance is analyzed when different parameters are selected.

Keywords: Mechanical vibration monitoring, Wireless sensor networks, Sparse Bayes, Monitoring nodes

1 Introduction

Vibration fault monitoring technology is to understand the state of the overall mechanical equipment or local mechanical parts during operation by analyzing the mechanical vibration signals collected by the sensors. This technology is a technology used to discover the early failure of mechanical equipment or predict the development trend of mechanical equipment failure [1]. Modern large-scale electromechanical equipment usually contains many rotating mechanical structures. Rolling bearings are the most commonly used components and play a very critical role in rotating machinery [2]. The health of rolling bearings greatly affects the operating state of the entire mechanical equipment [3]. When the rolling bearing fails, it will directly reduce the stability of the entire mechanical equipment and affect the working efficiency, and even a serious production accident occurs [4]. Therefore, it is very important to monitor the running status of bearings in real time through the mechanical equipment status monitoring system

[5]. The mechanical equipment condition monitoring system performs feature extraction and pattern recognition by collecting physical quantity data during the operation of the equipment.

Common physical quantities include vibration signals, acoustic emission signals, temperature, and lubricant wear [6]. Vibration signals are easier to collect than other physical quantities and can better characterize the normal or faulty state of bearings during operation. Therefore, mechanical state detection systems based on vibration signal analysis are the most widely used [7]. The mechanical equipment condition monitoring system using wired connection is widely used in many large-scale equipment detection and process control [8]. However, the traditional wired connection method has some shortcomings. The wired connection system requires additional connection cables, so the signal is susceptible to interference during transmission. If the transmission distance is long, the lengthy cable will cause problems such as increased installation cost and maintenance cost [9]. In recent years, the development of wireless sensor networks has broken this wired connection model.

Faced with various problems of wired rotating machinery vibration monitoring system under some special environmental conditions, a new type of mechanical vibration monitoring method based on wireless sensor network has entered people's research field [10]. The emergence of this new monitoring solution is due to the rapid development of embedded systems, wireless networks, and integrated hardware circuits in recent decades, which has reduced the cost and power consumption of wireless sensor networks and has broken through the barriers to the development of wireless sensor networks [11]. The wireless sensor network monitoring mode is a novel technical method for acquiring vibration signals. It uses a large number of distributed sensor nodes to self-network to construct a wireless data transmission method, thereby making up for the traditional wired monitoring system in some special insufficient circumstances [12]. Therefore, this paper proposes optimization techniques for mechanical vibration monitoring and signal processing based on wireless sensor networks. By combining the hardware design of the wireless sensor monitoring system and the signal processing optimization technology, the mechanical vibration monitoring technical solution is studied.

The rest of this paper is organized as follows. Section 2 discusses methods, followed by the experiment discussed in Sect. 3. The results are discussed in Sect. 4. Section 5 concludes the paper with summary and future research directions.

2 Methods

The hardware of the vibration monitoring system for rotating machinery based on wireless sensor network mainly includes two parts: wireless sensor network monitoring node and wireless sensor network base station node. The wireless sensor network monitoring node is generally composed of five parts: control center, data collection, data storage, radio frequency transmission, and power supply [13]. The node is responsible for collecting and digitizing the vibration and other information of the rotating machinery and then transmitting the information to the base station node by wireless transmission. The base station node of the wireless sensor network is mainly composed of five parts: control center, data storage, radio frequency transmission, Ethernet communication, and power supply. The main function of the base station is to gather, classify, and package the

information collected by the nodes joining the wireless sensor network and then transmit the data of each node to the host computer via Ethernet for data processing, display, and storage.

2.1 Overall design

The wireless monitoring system platform designed in this subject can be applied to the vibration monitoring of rotating machinery equipment and can even be widely applied to the vibration monitoring of other types of equipment through simple upgrades. The monitoring nodes in the system platform are used to obtain device status information. To intuitively understand the operating status of the device, the acquired device status information must also be read and displayed [14].

This requires the use of wireless networks to achieve data transmission and host computer software to display monitoring information. Through the design and analysis of the platform, the overall structure of the system is mainly composed of three parts: wireless sensor network monitoring node, wireless sensor network monitoring base station, and wireless sensor network host computer monitoring software. The structure diagram of a single wireless star network monitoring hardware platform is shown in Fig. 1.

The monitoring node installed on the rotating machine obtains the operating information of the rotating machine and transmits it to the base station node using radio frequency communication. The base station node uses Ethernet to transmit the received operating information to the monitoring host for visual monitoring [15]. The upper computer in the upper computer monitoring software is the data center of the entire hardware system. The base station node can receive the control commands of the upper computer software and then send it to the target monitoring node through radio frequency communication. The user can also observe the entire monitoring area intuitively through the monitoring host monitoring data and analyze the data through the computer to understand the running status of rotating machinery [16].

The wireless vibration monitoring network uses a star network structure, which includes a network center and multiple network nodes. The wireless sensor network monitoring base station is the network center, and the wireless sensor network

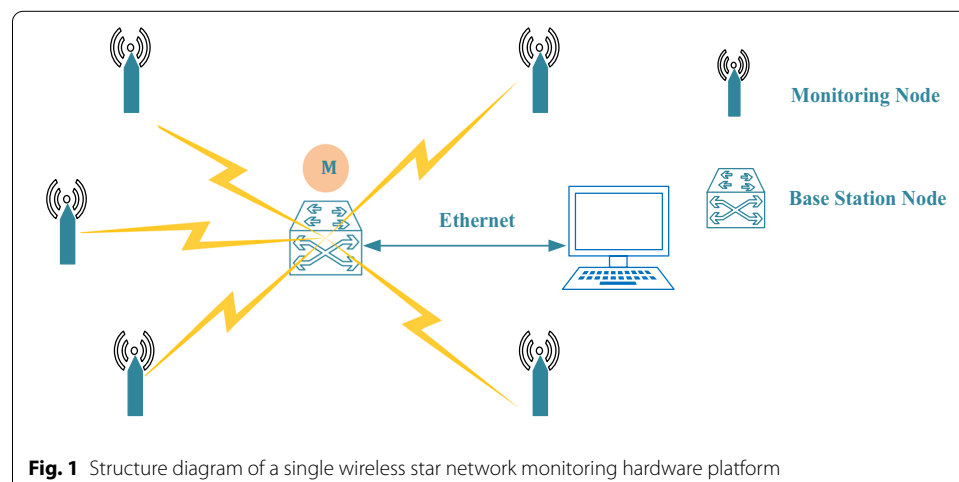


Fig. 1 Structure diagram of a single wireless star network monitoring hardware platform

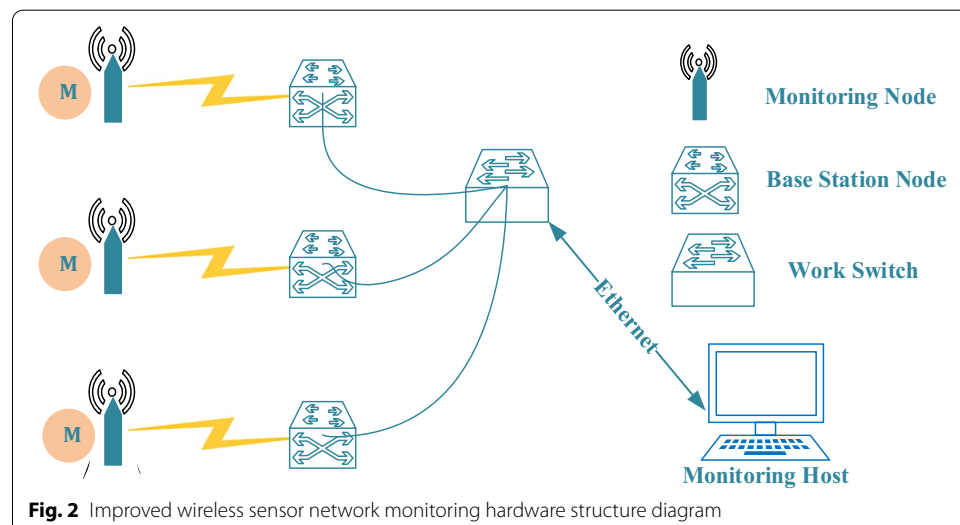
monitoring node is the network node to form the first-level wireless star network structure [17]. The second-level star network structure is networked by wire. It uses the monitoring host as the network center and the wireless sensor network monitoring base station as the node. The system transmits the monitoring data to the host computer through a two-level star network structure combining wireless and wired. The structure diagram of the improved wireless sensor network monitoring hardware is shown in Fig. 2.

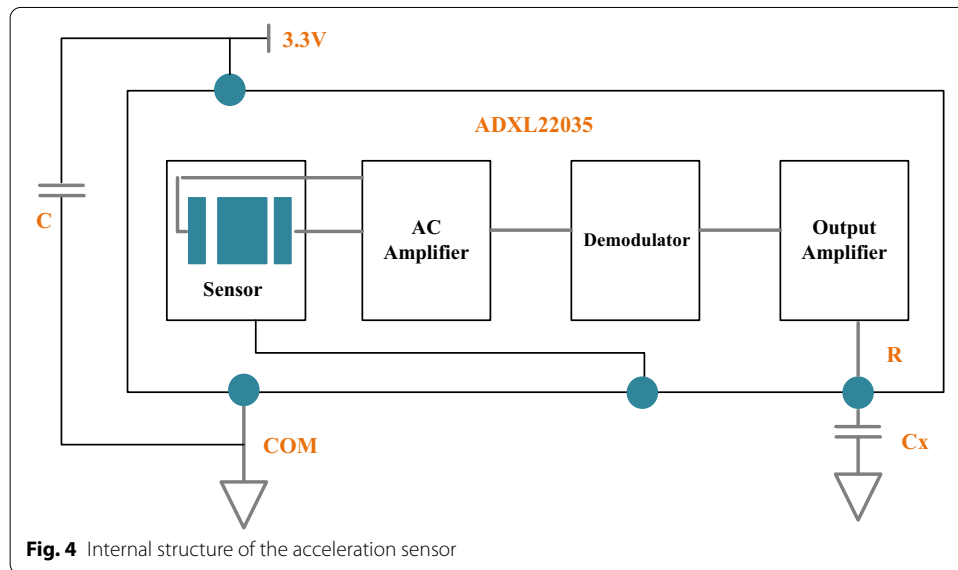
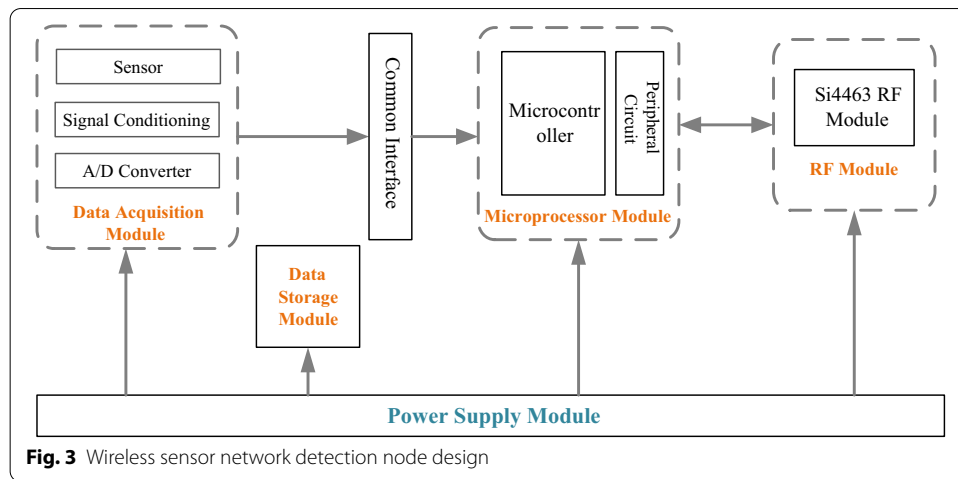
2.2 Design of wireless vibration monitoring node

2.2.1 Overall scheme design of monitoring node

The wireless rotating machinery vibration monitoring node uses ST's Cortex-M4 core 32-bit processor STM32F405RG as the core processor of the monitoring node. The wireless radio frequency takes Silicon Labs' Si4463 as the core and is equipped with Analog Devices' high-precision 16-bit A/D converter and MEMS acceleration sensor as the signal acquisition front end [17]. In addition, there are large-capacity flash storage modules and high-efficiency power supply modules as auxiliary.

Due to the higher accuracy and sampling rate required for vibration monitoring of rotating machinery, a large amount of data will be generated during the monitoring process. In response to the large power consumption problems of data storage, computing, and RF data transmission caused by large amounts of data, the monitoring nodes designed must have higher computing power, lower energy consumption, and superior storage capacity [18]. The overall design of the wireless rotating machinery vibration monitoring node is shown in Fig. 3. The wireless monitoring node consists of five parts: control center, data collection, data storage, radio frequency transmission, and power supply [19, 20]. The design adopts the concept of modularization, which is conducive to the addition and deletion of different functional modules, increases the flexibility of the equipment, and facilitates the upgrading and transformation of the equipment.





2.2.2 Data acquisition module

The data acquisition module circuit designed in this paper includes two parts: the sensor part and the signal conditioning conversion part. The sensor is the source of monitoring data for the monitoring system and must meet the characteristics of large range, wide bandwidth, and low power consumption required by mechanical vibration monitoring [21]. Because only digital signals can be processed and analyzed in the microprocessor system, and the ADXL2203 5 acceleration sensor output is an analog voltage signal, the voltage signal output by the general sensor will not meet the requirements of the AD input signal and must go through the signal conditioning module. And input to the A/D converter for digitization [22]. The internal structure of the acceleration sensor is shown in Fig. 4.

The sensing part needs to measure the vibration parameters of the device, and the sensor module is required to have the characteristics of small size, low power consumption, and simple circuit [23]. The frequency component of mechanical vibration is related to

the specific mechanical structure. The vibration signal of a typical mechanical structure often contains rich frequency components ranging from tens of hertz to several thousand hertz. Therefore, the vibration sensor needs to have a large bandwidth. The node in this paper adopts the high-performance 1VIMS vibration acceleration sensor ADXL2203 5 from Analog Devices [17].

3 Experiment

The sampling process is a very important part of digital signal processing. In order to ensure that important information in the original signal is not lost, the sampling process must follow the Nyquist sampling theorem, that is, the sampling frequency must be twice the bandwidth of the original analog signal. If further compression of the original sampled data is required, the common method is to perform sparse transformation on the original signal, discard the smaller coefficients in the transform domain signal, only retain the larger coefficients with the most information, and then decode the signal at the decoding end to perform reconstruction [1].

This chapter studies the vibration characteristics of rotating machinery, improves the traditional reconstruction algorithm, and proposes a compressed sensing reconstruction method based on block sparse Bayesian learning [24]. This chapter first studies the block sparse structure model, and several typical reconstruction algorithms using the block sparse structure model, analyzes the characteristics of the mechanical vibration signal in the transform domain, and verifies the feasibility of the block sparse structure model by analyzing the actual signal waveform. Secondly, the theoretical framework and hyperparameter estimation method of block sparse Bayesian learning and reconstruction algorithm are studied, and the use of block sparse Bayesian learning for compressed sensing reconstruction of rotating machinery vibration signals is proposed [25]. The compressed sensing method is used to process the bearing vibration signal, and the performance of different reconstruction algorithms is compared, which proves that the block sparse Bayesian learning method has better reconstruction accuracy than the traditional compression sensing reconstruction algorithm [26, 27].

3.1 Structural characteristics of the signal

The signal type studied in this paper is the vibration signal of rotating machinery, which is a typical one-dimensional signal. Generally, the actual one-dimensional engineering signals have obvious aggregation characteristics in the sparse signals in the transform domain, so it is reasonable to use the block sparse structure model to describe the vibration signals of rotating machinery [28, 29]. The block structure of the signal can be expressed as a series of non-overlapping coefficient blocks. Different vibration signals were analyzed to verify the block sparse characteristics of the vibration signals, and a preliminary exploration was made for the combination of vibration signals and compressed sensing of rotating machinery. In this section, the vibration signal with a load of 2hp, normal type, and three faults is selected at 800 points each [30]. The original signal has a very complex waveform in the time domain, but it has an obvious block sparse structure in the frequency domain, and when a fault exists, the larger coefficients are concentrated in the middle-frequency band. The signal has block sparse characteristics in the frequency domain and is related to the bearing vibration principle. 0 to 2000 Hz

can be regarded as a low-frequency band. The low-frequency band mainly includes the ripple error of the bearing processing surface, the frequency of vibration caused by the assembly position error, and the characteristic frequency of the fault [31, 32].

In the low-frequency band, the original vibration signal is particularly susceptible to noise interference, and the energy is very low. 2000 Hz to 4000 Hz can be regarded as an intermediate-frequency band. When the bearing fails, the signal energy in the mid-band is very high. This is mainly due to the existence of a bearing surface failure. When the bearing rotates past a failure point, it will cause an impact. The impulse signal is very short in time, and the spectrum range is particularly wide [33, 34]. The inherent vibration frequency of the bearing is generally within the frequency range of the fault impact signal. Therefore, the impact signal will cause the resonance of the bearing, which is very strong. When the bearing is fault-free, the resonance will not be excited because there is no impact signal, so the normal signal has almost no energy in the middle-frequency band. High-frequency band above 4000 kHz usually contains the high-frequency band spectrum caused by fault impact and may also contain some high-frequency noise, usually the energy is the lowest [35].

3.2 Sparse Bayesian algorithm

Bayesian algorithm is one of the commonly used algorithms in machine learning, mainly used for classification problems [36]. It mainly refers to that under the given conditions of the training data set, first, based on the assumption of the conditional independence of the feature variables, the joint probability distribution of input and output is obtained [37]. Then, based on this model, the input instance features are used to find the maximum posterior probability output using Bayes' theorem.

Let x be the input n -dimensional feature variable, and set $y \in \{c_1, c_2, \dots, c_n\}$ as input, X is a random variable on the input space, and Y is a random variable on the output space. The joint probability distribution of X and Y is $P(X, Y)$, and $P(X, Y)$ independently and identically generates the training data set.

$$T = \{(x_1, y_1), (x_2, y_2), \dots, (x_N, y_N)\} \quad (1)$$

Then, from the Bayesian formula:

$$P(Y = c_k | X = x) = \frac{P(X = x | Y = c_k)P(Y = c_k)}{\sum_{k=1}^K P(X = x | Y = c_k)P(Y = c_k)} \quad (2)$$

Naive Bayes has constructed conditional independence for conditional probability, namely:

$$P(X = x | Y = c_k) = P(X^{(1)} = x^{(1)}, X^{(2)} = x^{(2)}, \dots, X^{(n)} = x^{(n)} | Y = c_k) \quad (3)$$

The probability $p(y = 1 | x, \theta)$ represents the probability that y belongs to 1 given the characteristic variable x , and $h_\theta(x) = p(y = 1 | x, \theta)$, then there are models:

$$h_\theta(x) = [1 + \exp(-\theta^T x)]^{-1} \quad (4)$$

in which $\theta = \{\theta_0, \theta_1, \dots, \theta_p\}$ represents the coefficient value corresponding to each feature, θ value. It can be obtained by solving the maximum likelihood estimation function.

Assuming that each sample in the data set is independent of each other, the likelihood function is:

$$l(\theta) = \prod_{i=1}^n [h_{\theta}(x)]^{y_i} \cdot [1 - h_{\theta}(x)]^{1-y_i} \quad (5)$$

The basic formula of the Naive Bayes algorithm is shown in Eq. (6), and its meaning is the probability of the output category A given the instance Y .

$$P(Y = c_k / X = x) = \frac{\prod_{j=1}^n P(X^{(j)} = x^{(j)} / Y = c_k) P(Y = c_k)}{\sum_{k=1}^K (Y = c_k) \prod_{j=1}^n P(X^{(j)} = x^{(j)} / Y = c_k)} \quad (6)$$

In practical applications, when classifying feature instances, we select the final category with the largest probability value, which can be formalized as Eq. (7).

$$y = f(x) = \arg \max \frac{\prod_{j=1}^n P(X^{(j)} = x^{(j)} / Y = c_k) P(Y = c_k)}{\sum_{k=1}^K (Y = c_k) \prod_{j=1}^n P(X^{(j)} = x^{(j)} / Y = c_k)} \quad (7)$$

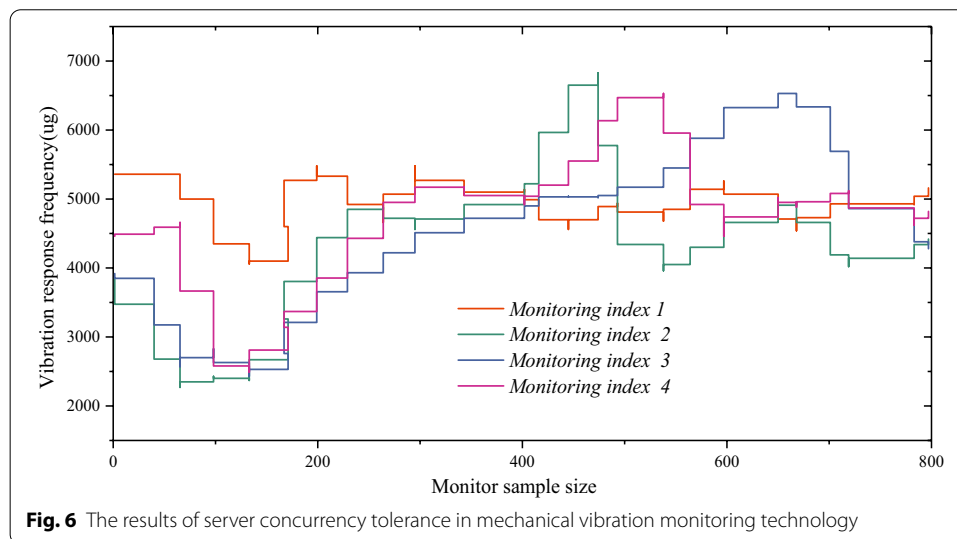
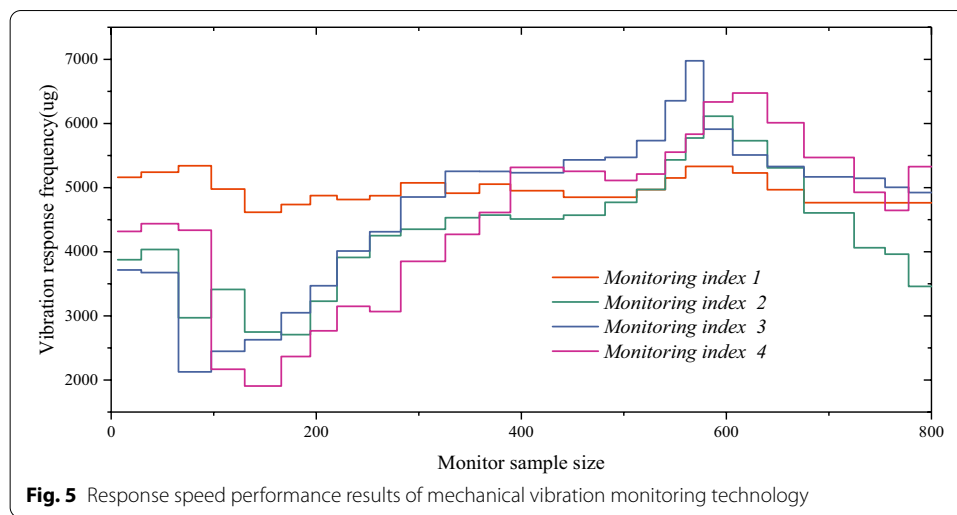
4 Results

In order to verify the high-precision reconstruction performance of the sparse Bayesian algorithm, experiments were carried out on the vibration signal processing method of rotating machinery based on compression sensing. The experimental data are a fault signal with a running load of 2hp, and the length of all experimental data is unified to 800. This section mainly conducts comparative experiments on reconstruction algorithms. Therefore, in order to avoid the influence of different forms of the sparse representation dictionary on the reconstruction accuracy, firstly perform sparse transformation on the time domain signal to obtain transform domain coefficients and then use Gaussian random matrix to transform domain coefficients for projection observation. Finally, a reconstruction algorithm is used to reconstruct transform domain coefficients from low-dimensional observation vectors, and finally an inverse transform method is used to reconstruct the original time domain signal. Projection observation using the observation matrix can reduce the length of the original data and use the signal frequency to evaluate the degree of data compression and optimization.

4.1 Technical performance test

In order to verify the reliability of the parameters of the mechanical vibration monitoring technology in actual use, we have organized various types of system tests. In the case that the function meets the business, the system also needs to meet the requirements of performance indicators such as response speed and server concurrent affordability. This system uses the Siege framework to perform performance tests and uses Noah to monitor various performance indicators. Figure 5 shows the response speed performance results of mechanical vibration monitoring technology. Figure 6 shows the results of server concurrency tolerance in mechanical vibration monitoring technology.

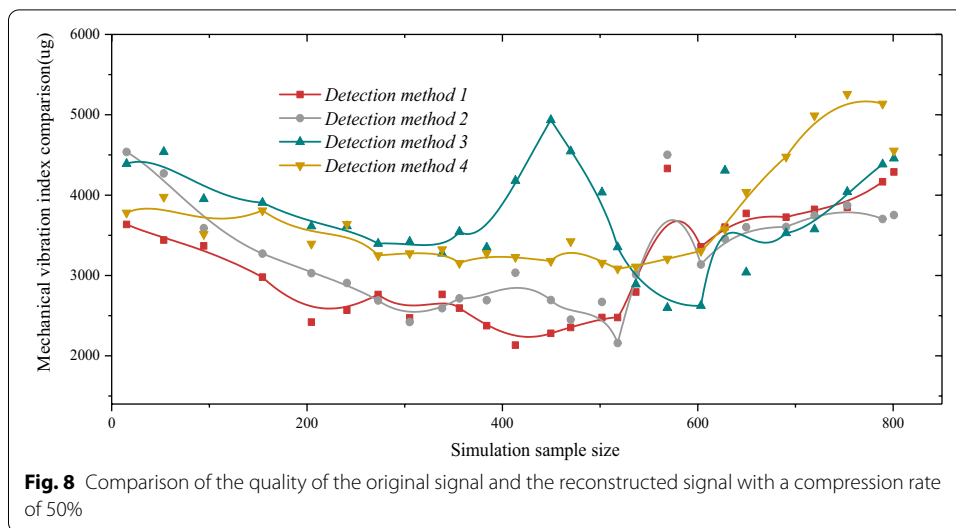
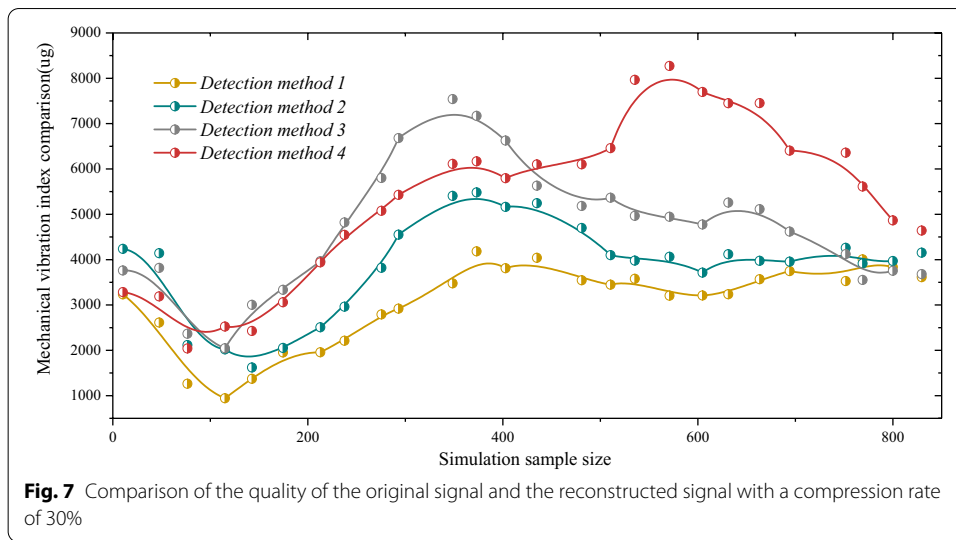
In the process of system performance testing, the two indicators of system response time and packet loss rate are used to test the concurrent performance of the system and



the performance of responding to customers. Limited to the network environment and server performance have a greater impact on performance indicators, the network environment during the test is selected as the internal network, and the server is a stand-alone server with a brand-new system and a cluster with two stand-alone servers.

4.2 Comparison of sparse Bayesian learning and other algorithms

In the previous chapter, in addition to introducing the concept of block sparse structure, several reconstruction algorithms using signal block structure were mentioned, including group LASSO, block OMP, group BP, etc. This group of experiments compares the reconstruction performance of sparse Bayes and other block-based sparse structure algorithms. The experimental signal is the bearing outer ring fault signal. During the experiment, except for the sparse Bayesian algorithm, other reconstruction algorithms need to set very complicated prior conditions, which will not be discussed in detail. Figure 7 shows a comparison of original signal and reconstructed



signal quality with a compression rate of 30%, and Fig. 8 shows a comparison of original signal and reconstructed signal quality with a compression rate of 50%.

It can be seen from Figs. 7 and 8 that the size of the original signal and the compression ratio has a very small impact on the reconstruction performance and can be ignored, and it can be considered that the sparse Bayesian algorithm is insensitive to the signal block structure. This is the advantage of this algorithm compared to other reconstruction algorithms based on block sparse structure. Before performing calculations, other types of algorithms must first set the block size that matches the signal type, otherwise the reconstruction error will be very large. However, the block structure information of the signal may be unknown in the actual signal processing, and only the sparse Bayesian algorithm can still reconstruct the signal with high accuracy without knowing the block structure of the signal.

Through the above experimental results, it can be observed that the four reconstruction algorithms based on fast sparse structure have no advantage, and even the reconstruction effect is even worse. This problem can be analyzed from two perspectives. First of all, although the energy of the signal has obvious concentration characteristics, it is not an ideal block structure, and there are still many small coefficients at other locations, and four reconstruction algorithms based on block sparse structure use simulation in a noise-free environment. Signal experiments are not good for actual complex signal processing. Secondly, these four kinds of block structure reconstruction algorithms require many prior conditions. Each reconstruction parameter setting needs to conform to the signal characteristics; obviously, the structure of the signal is different. This leads to a very large difference between the two transform domain reconstructed signals. In short, relying too much on the prior conditions will make the algorithm based on the sparse structure of the signal block inferior to the traditional algorithm in practical applications. Through a large number of experiments, the reconstruction performance of the block sparse Bayesian learning method and the existing reconstruction algorithm is compared. In addition, the denoising effect of block sparse Bayesian learning framework is studied. When studying the influence of the signal block structure on the reconstruction algorithm, an important conclusion is drawn through experiments, that is, the influence of the signal block structure on the block sparse Bayesian learning algorithm is negligible, which brings us new enlightenment.

5 Discussion

The wireless vibration fault monitoring technology is to analyze the mechanical vibration signal collected by the sensor to understand the status of the rotating mechanical equipment during operation, and then transmit the monitoring information through the wireless sensor network. This paper analyzes the problems that the wireless sensor network needs to solve in the application of mechanical vibration monitoring, and designs a set of wireless sensor network vibration monitoring system suitable for rotating machinery to initially realize the status monitoring of mechanical equipment. This paper designs a vibration monitoring platform for wireless sensor networks suitable for rotating machinery. According to the design requirements, the hardware circuit design of module units such as data collection, data storage, wireless communication, and power supply unit of the monitoring node is realized.

In addition, the sparse Bayesian algorithm is proposed as a compressed sensing reconstruction algorithm for vibration signal processing. The experiment compares the difference in reconstruction accuracy between this method and the traditional reconstruction algorithm, and the effect of this method on the reconstruction performance is analyzed when selecting different parameters. Although some research results of mechanical vibration monitoring optimization methods have been achieved in this paper, with the continuous expansion of the wireless sensing field and the expansion of new technologies, mechanical vibration monitoring methods still have many problems worth studying. We will further explore mechanical vibration principles and new technologies to provide a scientific reference for the development of modern industry.

Abbreviation

ADC: Airborne digital computer.

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Authors' contributions

XL is responsible for the data collection and analysis of the experiment and writing of the paper, and YW is responsible for the guidance and revise of the writing of the paper. All authors read and approved the final manuscript.

Availability of data and materials

Data sharing is not applicable to this article as no data sets are generated or analyzed during the current study.

Competing interests

The authors declare that they have no competing interests.

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