Composite Fault Signal Detection Method of Electromechanical Equipment Based on Empirical Mode Decomposition

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Abstract. Aiming at the problem of low detection accuracy when the traditional method is used to detect the composite fault signal of electromechanical equipment, a method for detecting the composite fault signal of electromechanical equipment based on empirical mode decomposition is proposed. In this paper, the operation information of the electromechanical equipment is collected first, and then the complex signal is identified based on the empirical mode decomposition theory, and the location of the complex fault area of the electromechanical equipment is completed to improve the detection accuracy. Finally, experiments are used to prove the advanced nature of the proposed method. The experimental results show that the fault diagnosis accuracy of the proposed method for electromechanical equipment is higher than 75%, the response time is less than 40 ms, and the memory occupation is less than 5500 kB, all of which are superior to the traditional method and have certain application value.

Keywords: Empirical mode decomposition · Electromechanical equipment · Fault signal · Fault detection

1 Introduction

With the rapid development of science and technology, fault diagnosis of electromechanical equipment is a rapidly developing technology all over the world. Fault diagnosis of electromechanical equipment is to master the working state of the equipment in the operation process, find the hidden dangers in the operation process of electromechanical equipment in time, and ensure the operation safety. Although the fault diagnosis technology of electromechanical equipment still uses the traditional diagnosis methods, its technology development has been widely adopted today, but what we see is that the fault diagnosis technology of electromechanical equipment has not formed a complete theoretical system and corresponding effective diagnosis reference technical specifications [1]. The existing technologies are studied one by one for different electromechanical specific faults, which are neither representative nor normative. The diagnosis methods

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of electromechanical equipment faults are determined according to the type of fault, and the real theories and methods are rarely used in practice, There is no complete system to evaluate this theory and method. The accuracy of fault diagnosis of electromechanical equipment is also a key problem to be solved urgently in this technology. Only by improving the accuracy of fault diagnosis can we reduce the repair time and effectively reduce the economic loss [2]. However, the key to the accuracy of fault diagnosis is to determine the characteristics of the fault, which is a complex problem. Generally speaking, the failure of electromechanical equipment is not a separate failure. The failure may be diversified, including motor manufacturing technology, use of materials, installation, operation, maintenance, etc. In modern mass production, the use of electromechanical equipment is more and more widely, and the operation safety of electromechanical equipment has attracted more and more attention. Based on this, this paper introduces the empirical mode decomposition theory into it, and studies the detection method of the composite fault signal of electromechanical equipment. It first analyzes the fault information extraction structure of electromechanical equipment, completes the collection of composite fault signals, then identifies its signals based on empirical mode decomposition theory, and completes the division and location of its fault areas. Citing the empirical mode decomposition theory can improve the detection quality of composite signals, greatly improve its recognition accuracy, and play an important role in the fault diagnosis and location of electromechanical equipment. It is hoped that through the research in this paper, it can provide literature references for current electromechanical equipment fault identification.

2 Composite Fault Signal Detection of Electromechanical Equipment

2.1 Composite Fault Signal Identification of Electromechanical Equipment

At present, the common monitoring of the health status of electromechanical equipment basically belongs to qualitative analysis and alarm, which can not achieve fault diagnosis and detailed analysis of fault types. Through the in-depth study of vibration signal fault detection algorithm and the research of key technologies such as sensor technology, terminal equipment pair communication and mutual control in industrial Ethernet network structure, a real-time online fault diagnosis model is developed, Realize the full life cycle management and fault diagnosis of electromechanical equipment, so as to facilitate the maintenance personnel to find potential safety hazards as soon as possible and formulate maintenance plans, so as to ensure safe production. The model is composed of computer, power box, vibration monitoring substation, optical transceiver, vibration sensor, shaft temperature sensor and other equipment and host computer software [3]. The composition structure of the model is shown in the Fig. 1 below.

Under the EMD motor equipment architecture, the division of labor for the extraction of electromechanical fault information needs to be determined according to the specific situation and equipment performance [4]. In the extraction of electromechanical fault information, the intelligent terminal needs to work in the field of the device under test, so its performance is limited in many aspects. Considering the limited data processing capability of intelligent terminals, data processing tasks with high computational complexity

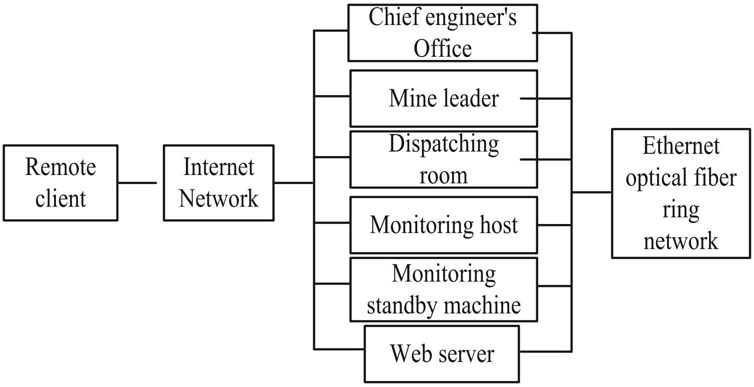

Fig. 1. Schematic diagram of electromechanical fault information extraction structure

require empirical mode decomposition equipment to complete. Empirical Mode Decomposition (EMD) plays an important role in EMD motor device architecture because of its computational power and ease of use [5]. The ultimate purpose of fault diagnosis of electromechanical equipment is fault classification. In this paper, several machine learning methods are used for classification. This relatively complex computational task requires empirical mode decomposition. Within the same inch, some key information obtained through calculation can also feed back some guidance and improvement instructions to the terminal. The operation steps of the equipment fault information detection instruction are as follows (Fig. 2).

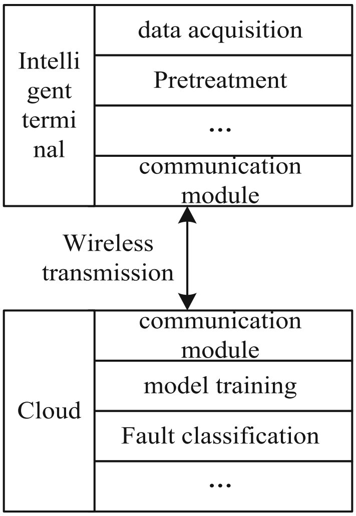

Fig. 2. Operation steps of equipment fault information detection instruction

General motor failures can be intuitively perceived as large vibrations and irregular noises, which may be caused by different installation techniques and materials used. The occurrence of motor failure is divided into continuous and indirect. Therefore, the function, quality and precision of the testing instrument will lead to the accuracy of the diagnosis. Mastering the fault diagnosis technology of electromechanical equipment can provide a reliable basis for the maintenance of electromechanical equipment, avoid economic losses caused by long maintenance time, and ensure the safe operation of electromechanical equipment. In this paper, FPGA and dual-core DSP + ARM9 are used for co-processing to collect, process, display, communicate, receive, process and respond to the commands of the monitoring host. Due to equipment failure, the vibration signal is relatively weak and susceptible to interference from other signals. The acquisition and processing of vibration signals in substations is the core part of the model, and the structure diagram of the data acquisition circuit is shown in the Fig. 3.

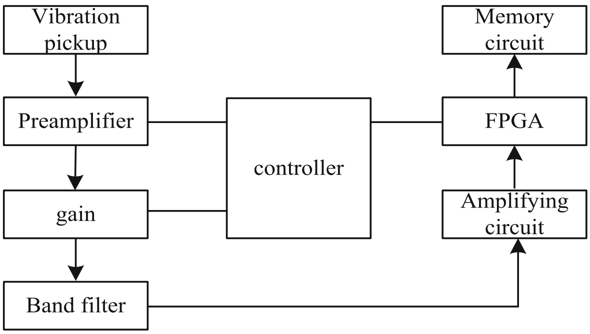

Fig. 3. Structure diagram of vibration signal acquisition circuit

The signal processing flow is that the sensor is used to collect vibration information, the signal is amplified by the preamplifier, the signal is filtered by 4-order low-pass and high pass through gain adjustment, and then amplified twice. The cooperative controller composed of DSP and ARM9 performs signal A/D conversion and storage through FPGA. The hard storage mode of FPGA greatly improves the real-time performance and work efficiency. On the monitoring host, the middleware defines the plant area, equipment name and type, measuring point name and type. This process is called configuration; On the monitoring host, DAQ software synchronizes the configuration information from the middleware, and downloads the configuration information generated by the corresponding channel number of each measuring point to the substation in DAQ. The substation must work, collect and upload data according to the configuration information; When the equipment connected to the substation changes, it must be reconfigured.

2.2 Location Algorithm of Abnormal Area of Electromechanical Equipment Fault Signal

Among the commonly used signals for fault detection at present, noise, current, voltage and vibration signals are particularly favored by scientific researchers. The reason is that these kinds of signals are the most convenient to collect and can reflect the current operation state of electromechanical equipment to a certain extent. The characteristics of these four kinds of signals are shown in the table [6] (Table 1).

Table 1. Performance comparison of different data types

Attribute	Signal type			
	Noise	Electric current	Voltage	Vibration signal
Is it intrusive	Non intrusive	Non intrusive	Intrusive	Non intrusive
Fault type reflection	mechanical failure	Electrical fault	Electrical fault	Mechanical and electrical faults
Fault prediction time in advance	Several weeks before the failure occurs	Several weeks before the failure occurs	Several weeks before the failure occurs	Several weeks before the failure occurs
Scope of application	Leakage of gas, liquid and vacuum equipment	Failure and power consumption of electromechanical equipment	Failure and power consumption of electromechanical equipment	Rotating electromechanical and mechanical equipment failure

Through the experimental comparison of four original data signals, this paper studies whether they are intrusive, reflect the fault type, scope of application and prediction time in advance. At the same time, considering the needs of practical production and application, vibration signal is the most suitable data type for fault diagnosis and prediction of electromechanical equipment. The detection of vibration signal is mainly to detect phase, frequency and amplitude, The most important is fast and accurate fault detection. At present, fault detection is mostly realized by hardware equipment, but the price of high-precision fault detection hardware equipment is very high, which is not suitable for large-scale network application of underground equipment. Therefore, the research on high-precision and fast software fault detection technology is the key to the success of the project [7]. Empirical mode decomposition can transform the original signal between time domain and frequency domain to find a more convenient method of data analysis. In the field of signal processing or data processing, fast empirical mode decomposition is a typical time-frequency domain decomposition method. From the root, HT is a method to quickly calculate discrete empirical mode decomposition. This fast calculation method is more suitable for modern computers to carry out empirical mode decomposition analysis of data. 130fft is not only a fast algorithm of DFT, The definition is also derived from DHT. The definition of FFT is given below. The definition of process DFT is:

$$X_k = \sum \mathrm{x}_{\mathrm{N}-1} e^{-2\pi \frac{1}{N}} \tag{1}$$

where, $\mathrm{x}_0, \mathrm{x}_1, \ldots, \mathrm{x}_{\mathrm{N}-1}$ is a complex number, and its complexity is calculated as e according to its definition. Centralize the data sample $N = \{x_1, x_2, \ldots, x_n\}$, and assume that the new coordinate system after orthogonal decomposition is $\{w_1, w_2, ..., w_a\}$, z_i^T is the orthogonal basis vector. If the dimension of the data space after dimensionality reduction is a, the original sample in the new coordinate system is μ, the original data sample point x, and the space between the reconstructed data sample point cage is:

$$\sum_{i=1}^{m} \left\| \sum_{j=1}^{d'} z_{ij} x_i \right\|_2^2 = \mu \sum_{i=1}^{m} z_i^t N - 2 \sum_{i=1}^{m} z_i^t w_a + a \tag{2}$$

If the distance from all sample points to the hyperplane is close enough to meet the best reconstruction and minimize the spacing, then

$$\begin{aligned} \Delta W &= \sum_{i=1}^{m} \left\| \sum_{j=1}^{d'} z_{ij} x_i \right\|_2^2 \min_W -\mathrm{tr}\left(W^T \left(\sum_{i=1}^{m} x_i x_i^T \right) W \right) \\ &= \sum_{i=1}^{m} \left\| \sum_{j=1}^{d'} z_{ij} x_i \right\|_2^2 \min_W -\mathrm{tr}\left(W^T X X^T W \right) \end{aligned} \tag{3}$$

The traditional software fault detection algorithm can not be applied to the single chip microcomputer model because of its complex operation structure, and the operation speed is relatively slow. The project studies a fault detection algorithm based on empirical mode decomposition, which is applied to the embedded model for rapid fault detection, reduces the application cost, and lays the foundation for the wide application of technology. Consider the following sinusoidal signals with amplitude A, period t and initial phase φ:

$$x(t) = Ae^{-2\pi \frac{1}{N}} - \Delta W \sin\left(2\pi \frac{1}{N} t + \varphi \right) \tag{4}$$

The standard sinusoidal signal of the same frequency is:

$$y(t) = \sin\left(2\pi \frac{1}{T} - e^{-2\pi \frac{1}{N}} \right) \tag{5}$$

If the period is μ_x and the initial phase is μ_y, the cross covariance function is:

$$\mathrm{C_{xy}}(\tau) = \mathrm{E}[x(t) - \mu_x]\,\mathrm{E}\left[\left(\mathrm{y(t)} - \mu_y \right) \right] \tag{6}$$

where, P represents the Fourier transform function of the mean formula as follows:

$$\mathrm{P_{xy}}(\omega) = \int_{-}^{+\infty} \mathrm{C_{vy}}(\tau) \mathrm{e}^{-\omega t} - x(t) y(t) \tag{7}$$

This algorithm has high accuracy after test. The cross power spectrum operation method greatly improves the anti-interference ability. It has significant advantages in the application under the condition of narrow underground space and more interference [8]. In addition, the structure of the algorithm is relatively simple, which greatly reduces the consumption of computing resources, improves the computing speed, and provides conditions for the wide application of low-cost fault detection.

2.3 Realization of Fault Signal Detection of Electromechanical Equipment

According to the characteristics of periodic data and fault signals of electromechanical equipment, a fault signal detection algorithm of motor equipment based on empirical mode decomposition is proposed. The algorithm is divided into two parts: Empirical Mode Decomposition part and intelligent terminal part. The empirical mode decomposition part is mainly responsible for the division of data, the cache of effective data, the calculation of the optimal sliding window size and the judgment of fault signal. The intelligent terminal part is mainly responsible for the data exchange with the empirical mode decomposition end, According to the extraction results of fault signal information by empirical mode decomposition, locate the fault signal and detect the located fault signal [9]. After processing the original data, the extracted and dimensionally reduced feature vectors are transmitted to the. On the one hand, the amount of data transmission is reduced, on the other hand, the reliability of the data to be transmitted is increased. The support vector machine is used to classify the bearing fault feature data. The largest part of the consumption of computing resources is the calculation of the classification hyperplane and the classification process of the data. Putting this part of the calculation on the can greatly improve the accuracy and practical feasibility of classification [10]. And in the construction of fault feature database, in the process of fault diagnosis, constantly improve the feature database, and use new features to replace the old features, not only make the features up-to-date, but also keep the data in the feature database on a certain scale [11]. The establishment of model base makes the algorithm proposed in this paper no longer have one-time learning ability like the traditional sVIM fault feature classification algorithm. The algorithm proposed in this paper can be continuously improved

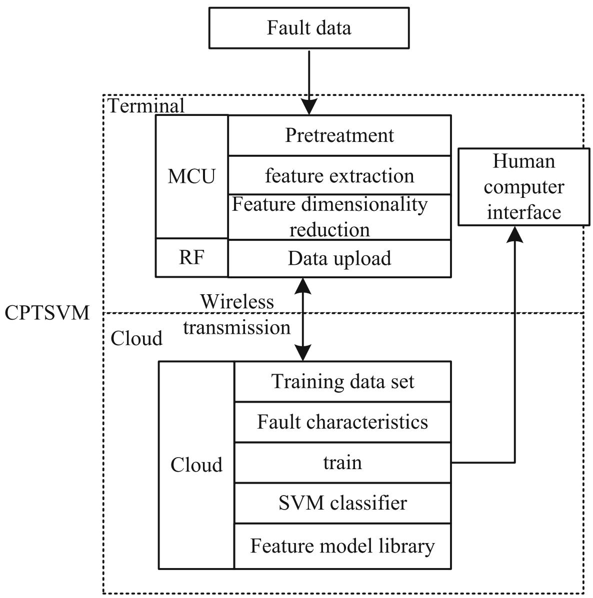

Fig. 4. Empirical mode decomposition motor equipment support vector machine model

and enriched in the process of operation, and has the ability of “lifelong learning”. As shown in the figure, the empirical mode decomposition motor equipment support vector machine model used in this paper (Fig. 4).

The empirical mode decomposition online training model adopts the structure of “offline training + online training online classification”. In the initial stage, the classified fault data are used to train the empirical mode decomposition model offline and establish the initial empirical mode decomposition model; Then start online fault diagnosis. The diagnosis results of the initial empirical mode decomposition model are notified to the site through the human-computer interface. After the staff check the fault on the spot, they are fed back to the model, and the fault feature vector is saved in the feature model library. The model counts the accuracy of diagnosis. When the accuracy is lower than the specified threshold, call the feature library for secondary training of the empirical mode decomposition model, That is, online training, while avoiding excessive resource occupation. The training process of empirical mode decomposition model is shown in the Fig. 5.

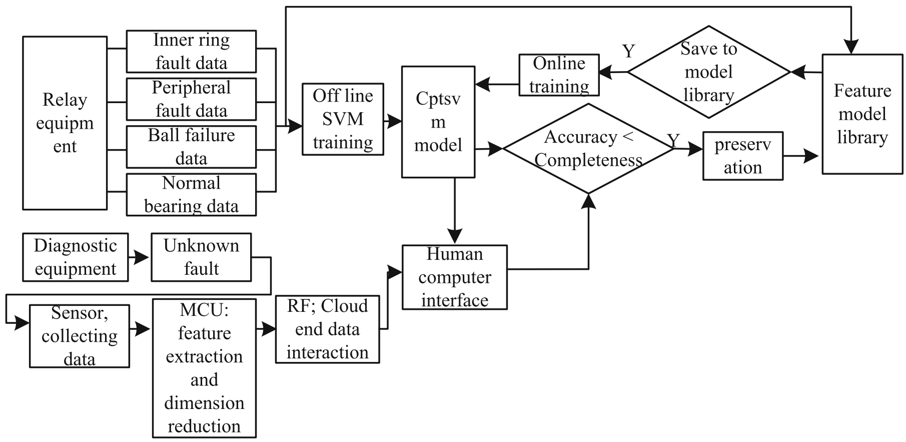

Fig. 5. Training process of fault detection model

The data release software adopts modular design and has various analysis maps. Through the map analysis, the maintenance personnel can fully grasp the operation and health status of the equipment. Through the overview of the unit, the overall operation of the equipment can be viewed in real time, and the data of each measuring point on the equipment can be displayed intuitively. Click the corresponding measuring point to enter the spectrum analysis interface of the measuring point. Through the diagnostic analysis interface, you can view the data and curves of the equipment in each time period, as well as the spectrum and diagnostic report. In order to effectively improve the accuracy of electromechanical equipment fault diagnosis results, the diagnosis model needs to calculate and analyze multiple electromechanical equipment operation signals through the electromechanical equipment fault detection model, and the detection result error will be less than the traditional calculation error. The accuracy of the test results of the electromechanical equipment fault detection model is significantly higher than that of the traditional fault diagnosis methods, which has strong diagnostic value and should be vigorously popularized. With the progress of science and technology, the traditional fault diagnosis technology of electromechanical equipment has a new development trend. The fault diagnosis of electromechanical equipment has integrated sensor technology, artificial intelligence technology, data processing technology and wireless communication technology, and gradually transformed into precision and multidimensional, diversified diagnosis theory and diagnosis model and intelligent diagnosis technology. Mature diagnostic technology will be quickly applied to socialist modernization and national defense security construction.

3 Analysis of Experimental Results

In order to fully verify the practicability of the proposed method, this paper firstly tests the performance of the detection algorithm, and then based on different load conditions and fault changes, the diagnostic accuracy of different equipment states changes, and finally selects the detection accuracy, detection time and operation occupancy. Three indicators of memory are used to test the performance of the proposed method and the comparison method. The experimental equipment uses Dell precision tower5810 server and the terminal equipment uses embedded intelligent terminal. In order to facilitate the experimental comparison and operation, this paper uses the simulated periodic flow data for the test, and adds the periodic gradual fault signal and noise interference signal for the test. The experiment is divided into two parts: the comparison of the parameters of the algorithm itself and the comparison of different algorithms to fully illustrate the effectiveness and superiority of the algorithm. According to the different sampling frequency of the sensor, it is determined that the number of data points added to the fault signal in each cycle is 10–20. The input k value range is determined according to the range of the fault signal. The accuracy of the algorithm with different K values is shown in the Fig. 6.

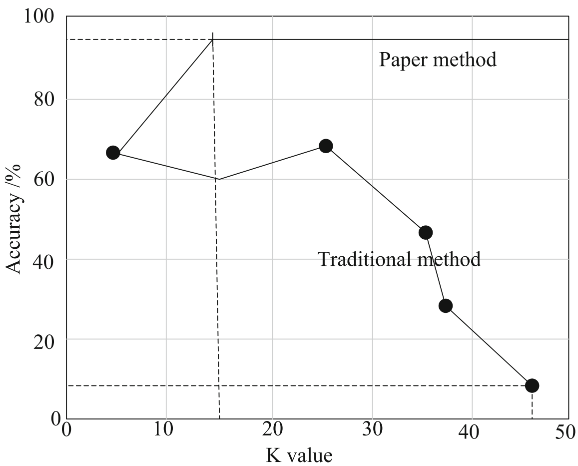

Fig. 6. Variation curve of algorithm accuracy with K value

It can be seen from the figure that the value of K is too large or too small, which will lead to the decline of the accuracy of the algorithm. According to the analysis of the detection results output by the algorithm, if the value of K is too small, it will lead to the algorithm misjudging some fault signals as normal data flow and reducing the detection rate; If the value of K is too large, the normal signal is easy to be misjudged as a fault signal, which increases the misjudgment rate, resulting in a sharp decline in the accuracy of the algorithm. According to the above analysis, the best K value should be between 10 and 15. During the operation of mechanical equipment, the equipment state may change, and the reasons include load change and mechanical damage caused by long-time operation of the equipment. The model solution proposed in this paper is helpful to reduce the diagnosis error caused by this kind of change to the diagnosis model. In this experiment, the data under different load conditions are collected as the change of load state, and the data under different fault diameters are collected as the mechanical wear caused by long-time operation. In order to use a large amount of data for the calculation of diagnosis accuracy, the “manual inspection” in the “algorithm description” part is replaced with a fault tag to judge whether the diagnosis is correct or not. The table shows the comparison between the accuracy of traditional off-line learning and online learning diagnosis proposed in this paper when the load change and fault size change are used to simulate the change of equipment state (Table 2 and table 3).

Table 2. Comparison of diagnostic accuracy after 20% load change

Test method	Fault classification accuracy/%				
	Normal	Inner ring fault	Outer ring fault	Ball failure	Total
Original accuracy	99.00	96.00	94.50	98.00	96.85
Online learning method	98.60	97.00	94.50	98.50	95.95
Offline learning method	93.60	81.50	90.50	95.00	92.00

Table 3. Comparison of diagnosis accuracy after 10% change of fault size

Test method	Fault classification accuracy/%				
	Normal	Inner ring fault	Outer ring fault	Ball failure	Total
Original accuracy	99.00	96.00	94.50	98.00	96.85
Online learning method	99.60	97.00	94.50	96.50	97.85
Offline learning method	97.60	82.00	78.50	90.00	87.89

The purpose of the experiment is to explore the accuracy of empirical mode decomposition fault detection algorithm (method 1). In order to make the conclusion of this experiment more persuasive, the conclusion is given by comparison. According to the different characteristics of fault signals and other signals, the signals are separated, and both include the detection of periodic fault signals. The comparison of the experimental results can better reflect the advantages of this algorithm (Fig. 7).

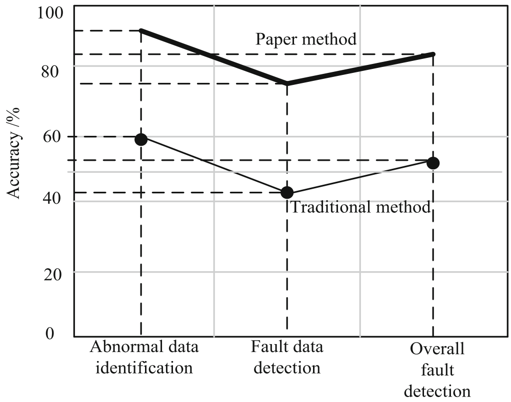

Fig. 7. Comparison of accuracy of different methods

It can be seen from the experimental data that the empirical mode decomposition data fault detection algorithm has the highest accuracy, and the test signal processing method based on cepstrum has the lowest detection accuracy. Although the test signal processing method based on cepstrum can highlight the small period signal through signal weighting, the influence of noise will also increase in the signal with low signal-to-noise ratio. Therefore, although it has good processing effect on the signal with high signal-to-noise ratio, its recognition degree for the signal segment containing a large amount of noise is not very high, resulting in the decline of the overall detection accuracy of this method; The empirical mode decomposition fault detection algorithm proposed in this paper makes full use of the periodic characteristics of fault signals, which can effectively separate noise signals and fault signals, so as to achieve high detection accuracy. In order to compare the execution efficiency of the algorithm, the length of time spent in the operation of the algorithm and the size of memory space are selected for comparison. The experimental data used are divided into five sections, each accounting for 20% of the data set. The average time and average memory space required for the three algorithms to run on the segmented data are counted respectively. The experimental results are shown in the Fig. 8 (Fig. 9).

It can be seen from the experimental data above that the fault signal detection algorithm of empirical mode decomposition motor equipment proposed in this paper is superior to the traditional algorithm in terms of running time and memory. The calculation speed of the proposed algorithm is obviously faster than the other two algorithms, so from the speed analysis, this algorithm is more suitable for the stream data processing with a large amount of data. It can be seen from the figure that the memory consumption of this algorithm is less than that of the other two algorithms, which proves that this method has high practicability and fully meets the research requirements.

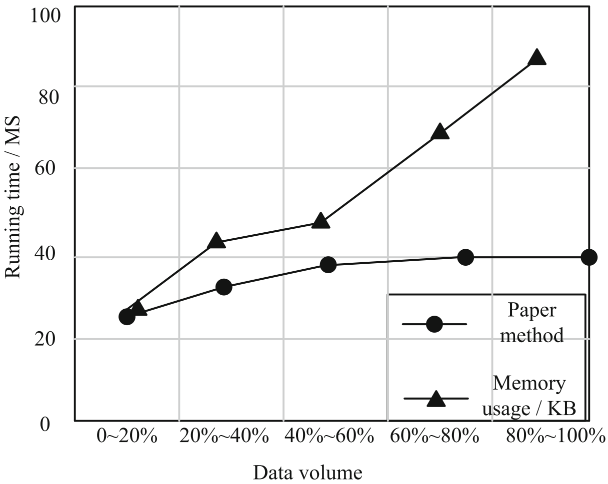

Fig. 8. Comparison of running time of different algorithms in different stages

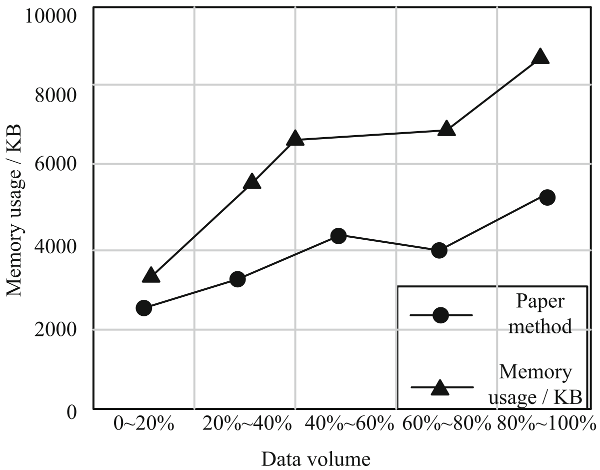

Fig. 9. Comparison of memory usage of different algorithms in different stages

4 Concluding Remarks

With the increasing application of large-scale electromechanical equipment, people's requirements for its fault detection technology are gradually increasing. In view of the existing problems such as difficulty in fault detection and positioning and long maintenance cycle, the research on high-efficiency electromechanical equipment fault diagnosis technology is of great significance for reducing maintenance workload, shortening failure time, and improving production efficiency Through the analysis of the research status of fault diagnosis technology, this paper studies and designs the fault detection algorithm based on empirical mode decomposition, and develops the vibration monitoring substation, vibration sensor, temperature sensor and host computer monitoring software based on FPGA and dual core controller, forming a set of electromechanical equipment fault diagnosis model. The model has been tested in Shanxi Tiandi Wangpo Coal Industry Co., Ltd. The operation of the model is stable and reliable. It can judge the operation state of the equipment in advance and give corresponding measures, which greatly reduces the workload of on-site maintenance and maintenance personnel and improves the efficiency of safe production.However, the model in this paper still has shortcomings, that is, it can only identify the faults of some electromechanical equipment, and cannot accurately identify the fault signals of large electromechanical equipment systems, which is also the next research goal.

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References

1. Zhao, Y.-B.: Research on multi-sensor fusion multi-fault signal monitoring of Marine turbine equipment. Ship Sci. Technol. **44**(17), 114–117 (2022)
2. Huang, W., Li, S., Mao, L., et al.: Research on multi-source sparse optimization method and its application in compound fault detection of gearbox. J. Mech. Eng. **57**(07), 87–99 (2021)
3. Wang, H., Wang, M., Song, L., et al.: Method of compound fault signal separation using double constraints non-negative matrix factorization. J. Vibr. Eng. **33**(03), 590–596 (2020)
4. Lian, J., Fang, S., Zhou, Y.F.: Model predictive control of the fuel cell cathode system based on state quantity estimation. Comput. Simul. **37**(07), 119–122 (2020)
5. Xiao, Y., Shen, Y., Yang, F., et al.: Fault state variables integral based open-circuit fault detection for power unit of cascaded h-bridge converter. Power Syst. Technol. **45**(11), 4213–4225 (2021)
6. Cui, R.H., Li, Z., Tong, D.-S.: Arc fault detection based on phase space reconstruction and principal component analysis in aviation power system. Proc. CSEE **41**(14), 5054–5065 (2021)
7. Chen, Y., Chen, Y., Liu, Z.-Q., et al.: A gear fault detection method based on a fiber bragg grating sensor. Chin. J. Lasers **47**(03), 232–241 (2020)
8. Liu, H., Wang, Y.-Y., Chen, W.-G., et al.: Fault detection for power transformer based on unsupervised concept drift recognition and dynamic graph embedding. Proc. CSEE **40**(13), 4358–4371 (2020)
9. Wang, B., Cui, X.: Detection method of arc high resistance grounding fault in resonant grounding system based on dynamic trajectory of volt-ampere characteristic. Proc. CSEE **41**(20), 6959–6968 (2021)
10. Yang, S.-Z., Xiang, W., Wen, J.: A fault protection scheme based on the difference of current-limiting reactor voltage for overhead MMC based DC grids. Proc. CSEE, **40**(04), 1196–1211+1411 (2020)