The Fault Monitoring Method Based on Vibration Signal for Crane System

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Abstract—**Manufacture industry has undergone transformation and upgrading, and the economy has developed rapidly in the world. Metallurgical cranes are important industrial tools to support the rapid development of manufacturing industry. The frequent occurrence of crane accidents has seriously affected the pace of manufacturing upgrades. Therefore, it is particularly important to conduct risk assessment and fault monitoring research for metallurgical cranes. In order to improve the efficiency of cranes and solve a series of safety problems caused by cranes failure, this paper proposes a kind of crane system fault monitoring method based on vibration signal analysis for crane failure mechanism, and realizes automatic identification of crane system failures by Naive Bayesian algorithm (NB).**

Keywords-Metallurgical cranes; system risk assessment; Naive Bayesian classfier; fault monitoring

I. INTRODUCTION

Cranes are important industrial tools that support the rapid development of manufacturing. If critical crane fails, it will affect the manufacturing and production of the company's products. How do we control the occurrence of crane failures? In addition to making the design of the crane itself more reasonable, it can also strengthen the monitoring of the work process. For a long time, academia and industry have done a lot of research on improving the safety of crane structures, but monitoring the failure of cranes has the same economic value. Nowadays, a large number of sensors start to apply to all aspects of our lives [1]. We can easily upload the received signals directly to the computer, and select the appropriate classification algorithm to classify the real-time monitoring data and quickly identify the status of the device. By applying this idea to the crane's fault identification, we can monitor the crane, reduce the occurrence of crane accidents and the cost of crane failure. Based on this idea, this paper proposes a simple and economical method for crane fault monitoring and diagnosis based on vibration signals.

II. THE PRINCIPLE OF VIBRATION SIGNAL ANALYSIS.

We found that some of the components are the main cause of vibration in the crane system[2]. Therefore, when we analyze the vibration signal characteristics of the crane system, it can realize by analyzing the vibration mechanism and vibration signal characteristics of the components such as bearing, motor and reducer.

A. Vibration Signal Analysis Feasibility Study

For the drive shaft, the motor, and the reducer, the vibration signal includes the structural characteristics and the vibration component caused by the fault[3]. Although the structure's characteristics and machining error has a certain periodicity, such vibrations have strong randomness, complex frequency components, and low amplitude, so we can ignore it. The random vibration generated by the surface ripple, surface roughness, geometric accuracy of the rolling elements and raceways.

However, after the fault, the collected signal will have periodic characteristics. Taking the bearing as an example, when the shaft fails, the vibration amplitude will increase greatly. After the fault occurs, it will produce a periodic variation [4][5]. The vibration waveform have large difference for component during normal operation and faulty parts. We can easily find this difference.

Therefore, it is feasible to use vibration signals for analysis to achieve its monitoring and fault diagnosis.

B. Sensor installation

In the actual monitoring process, in order to improve the accuracy of the results, it is necessary to consider the position of the sensor for data collection carefully. Firstly, we need to

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ensure the easy installation of the vibration sensor, then, it is necessary to make the transmission distance between the vibration source and the vibration pickup device as small as possible. That is to minimize the introduction of vibrational weakening or other vibrational components due to structural or other factors during the transfer.

III. VIBRATION SIGNAL ANALYSIS

A. Data noise reduction

The collected raw data is often noisy. In order to extract the signal components from the measured data, the data needs to reduce noise. In the process, we must use the characteristics of noise to maintain the signal components as much as possible. Based on our research, here, we choose a common frequency transformation method, Wavelet transform.

Wavelet transform (WT) is a new transform analysis method. It inherits and develops localization short-time Fourier transform. At the same time, it overcomes the shortcomings of window size and frequency variation, and can provide a change with frequency. The "Time-Frequency" window is an ideal tool for signal time-frequency analysis and processing, which helps to detect faults in time. In the crane system, the fault information is composed of low frequency band information and high frequency band information, so the selected mother wavelet needs to reflect the local characteristics of the signal very well. Choosing Daubechies (dbN) wavelet can achieve it[6]. The following figure shows the scale function and wavelet function of db4 wavelet, respectively.

Using wavelet transform to process the vibration signal, and then it is initialized and iteratively decomposed to filter out the uncorrelated vibration frequency. In this way, we can reach to reduce the noise effect. From the figure below, we can also observe that the vibration waveform has changed.

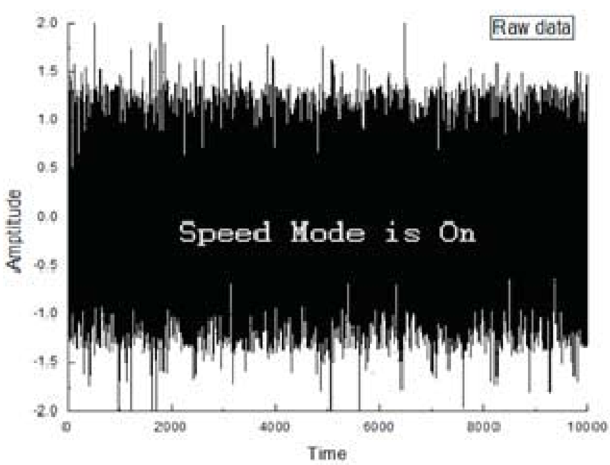

Figure 1. Raw data.

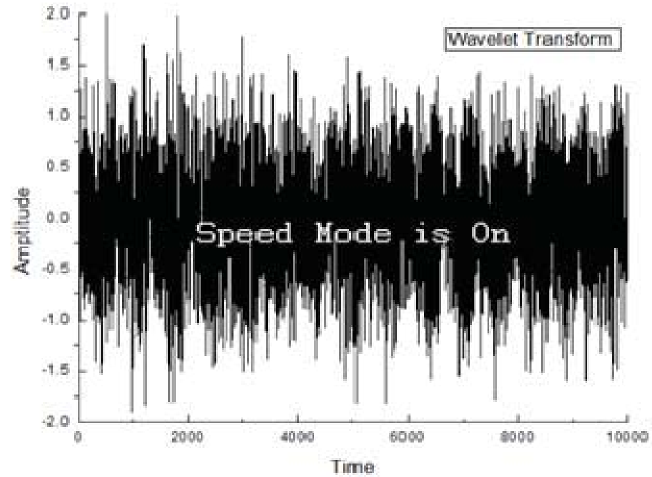

Figure 2. The waveform processed by wavelet transform.

Fourier transform is a common signal processing method. We transform the original signal into a frequency domain signal by triangulation, in this way we can find some characteristics of the signal more easily. Through the Fourier transform, converting the signal data into the spectrum format of the abscissa frequency and the ordinate amplitude from the time domain format of the abscissa time and the ordinate sample values[7].As shown in picture 5.

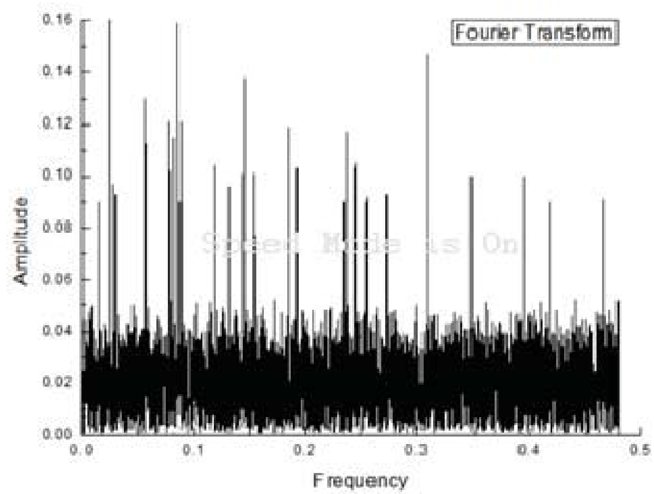

Figure 3. Wavelet function of db4 wavelet.

The spectrum peak of the spectrum when the equipment is faulty and normal is different, which provides a basis for fault diagnosis of the equipment. Using this obvious characteristic, the frequency domain signal obtained by Fourier transform is uploaded to the monitoring platform, and the spectral peak is used as the characteristic quantity of the signal input, and then the appropriate algorithm is used to monitor the fault. There are many ways to achieve this goal. Considering the common classification algorithm, this paper uses the naive Bayesian algorithm to achieve it.

IV. NAIVE BAYESIAN CLASSIFICATION ALGORITHM

A. Introduction to Naive Bayesian Algorithm

The naive Bayesian algorithm is a simple machine learning algorithm. The basic idea is to classify the to-category items, and to solve the probability of occurrence of each category under the condition of this occurrence[8][9]. The specific steps as follows:

1. Set $\chi=\{a_1,a_2,\ldots,a_m\}$ to a category to be classified, and each a_m is a feature attribute of χ.
2. There is a collection of categories for $C=\{y_1,y_2,\ldots,y_n\}$
3. And calculate the value of these quantities: $P((y_1)|x)$, $P((y_2)|x),\ldots, P((y_n)|x)$.

$$P((y_k)|x)=\max\{P((y_1)|x), P((y_2)|x),\ldots, P((y_n)|x)\}, x \in y_k.$$

B. Algorithm implementation process

According to the principle of Naïve Bayesian algorithm, we can design the following specific algorithm flow as follows:

- Dividing the collected vibration data into two categories, one is normal data as A, and the other is fault data as B. Firstly, collecting 50 groups of the two categories of vibration data as the training sample set, the peak of the selected vibration signal is set as the characteristic attribute.
- Using 50 sets of test data for algorithm verification, the naive Bayesian algorithm compares the characteristics of the test data with the features corresponding to the training set, and calculates the conditional probability of each feature attribute between the test data and each training data.
- Finally, returning the category that meets the highest conditional probability as the prediction classification of the test data. The basic flow chart is as follows:

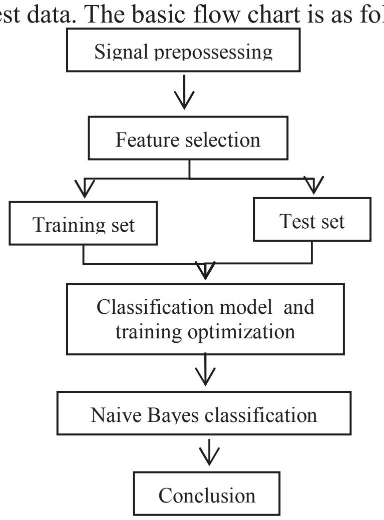

Figure 4. Algorithm flow chart.

If the peak of the vibration data to be tested can satisfy the category of the faultless data more, it means that the device can work properly and automatically classify into the normal data category, and vice versa is the fault data class. Realize whether the monitoring of the hoisting machinery system is in a fault state

Wavelet transform (WT) is a new transform analysis method. It inherits and develops localization short-time Fourier transform[10].At the same time, it overcomes the shortcomings of window size and frequency variation, and can provide a change with frequency. The "Time-Frequency" window is an ideal tool for signal time-frequency analysis and processing, which helps to detect faults in time. In the crane system, the fault information is composed of low frequency band information and high frequency band information, so the selected mother wavelet needs to reflect the local characteristics of the signal very well. Choosing Daubechies (dbN) wavelet can achieve it. The following figure shows the scale function and wavelet function of db4 wavelet, respectively.

C. Experimental design and results analysis

The experiment run on a PC with an Intel Core i5-4210M dual-core processor .3.2 GHz, 8 GB of memory, and Windows 10 operating system. The algorithm based on the PyCharm software platform, and the version of python is 3.6. Use scikit-learn as the training environment for naive Bayesian classifiers.

At the same time, in order to facilitate the evaluation of the results, this paper introduces the common machine learning algorithm evaluation indicators[11],[12]. As an evaluation index of the results, the evaluation indicators commonly used in the industry have precision (P), recall rate(R), F- Measure (F), the formula as follows:

$$P = \frac{S_0}{S_1} \tag{1}$$

$$R = \frac{S_0}{S_2} \tag{2}$$

$$F = \frac{2\times P\times R}{P+R} \tag{3}$$

S_0 is the number of groups with the correct classification, S_1 is the total number of groups, and S_2 is the number of groups of this class.

D. Experimental result

Summary of 50 sets of experimental data for testing, get the results as shown in the following table:

TABLE I. TEST RESULT SUMMARY TABLE

Data Types	Test Value		
	Actual number	*Correct number*	*Error number*
A	22	17	5
B	28	25	3
Total	50	42	8

According to the experimental results, after 50 sets of tests, we monitor successfully the status of 42 sets of data and we can calculate the value of the precision, recall rate, F-Measure,which is P=0.8400, R=0.7727, F=0.8051.

From the results, we can find that the algorithm can perform fault monitoring very well, so this method is feasible.

CONCLUSION

Aiming at the fault characteristics of the crane and the convenience of practical application. This paper proposes a simple and economical crane fault monitoring method, installs a suitable vibration sensor for the crane, collects real-time data and uploads it to the computer, and processes the original data through wavelet transform and Fourier transform, using normal and fault conditions. The difference in vibration frequency. Using the naive Bayesian algorithm and using the vibration peaks as feature quantities to classify the data. This paper uses the bearing experimental data published by Xi'an Jiaotong University and Sumyoung Technology Joint Laboratory to verify the results. It can be seen from the experimental results that the method can realize automatic identification of crane faults. If engineering application is applied, it can improve the efficiency of fault diagnosis and reduce the possibility of safety accidents caused by faults. This method greatly improves the reliability of equipment.

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