Research on Fast Separation Method of Motor Fault Signal Based on Wavelet Entropy

Jintian Yin[1,2], Li Liu[1,2](✉), Junfei Nie[1,2], Zhihua Peng[1,2], and Riheng Chen[1,2]

[1] Hunan Provincial Key Laboratory of Grids Operation and Control on Multi-Power Sources Area, Shaoyang University, Shaoyang 422000, China
yinjintian112@yeah.net
[2] School of Electrical Engineering, Shaoyang University, Shaoyang 422000, China

Abstract. The extraction of motor signals by traditional methods will be affected by multi-component signals and non-stationary signals, and the separation effect of motor fault signals is poor. Therefore, a fast separation method of motor fault signals based on wavelet entropy is proposed. Obtain the motor fault vibration signal, convert it to the frequency domain for solution, and denoise the motor fault vibration signal through three-layer wavelet packet decomposition. Based on wavelet entropy, the sliding window is set for simulation, and the optimal features are selected for extraction to quantitatively describe the time-frequency and energy distribution of motor fault transient vibration signal. The second-order VKF filter is selected to extract multiple components at the same time, so as to realize the separation of multi-component signals. Experimental results show that this method can effectively separate and extract motor fault signals, and can achieve good results under high noise intensity.

Keywords: Wavelet entropy · Motor failure · Fault signal · Rapid separation · Signal separation · Fault diagnosis

1 Introduction

In the industrial process, the safety and reliability of mechanical system determine the quality of products. Whether the faults can be identified and classified in time is the key to ensure the safe operation of the system and inhibit the deterioration of faults. As an important power equipment in various production fields, motor has the advantages of low price, relatively simple overall structure and reliability. It undertakes more than 80% of the kinetic energy output in the process of modern industrial and agricultural production. In the modern industrial system, with the rapid development of manufacturing digitization, real-time recording and perception of production and operation status and operation environment have been realized, and a large number of industrial time series data have been accumulated and are being generated. If the motor fails during the operation of the equipment, it will lead to unstable operation and sharp increase in energy consumption. In serious cases, it will even cause damage to the motor and equipment, which will affect

W. Fu and L. Yun (Eds.): ADHIP 2022, LNICST 469, pp. 14–25, 2023.
https://doi.org/10.1007/978-3-031-28867-8_2

the normal operation of the whole equipment. Sudden shutdown and maintenance must be carried out, resulting in problems such as slow production progress and economic loss. In the face of massive data, how to quickly extract the sensitive feature set of motor fault, accurately identify and classify it, and quickly separate the motor fault signal is the key to efficiently find motor fault and avoid serious damage. It is also the key research object of fault diagnosis.

At present, it can be divided into three categories: machine based, model-based and signal-based fault diagnosis. Wang Xin et al. Took a group of air-conditioning fault motors as the experimental object, built a motor fault diagnosis platform, carried out acoustic signal acquisition experiments on air-conditioning motors in four states, and classified the data set by using algorithm [1]. As a new structure depth learning algorithm, algorithm can classify motor fault acoustic signals well. Cai Wenwei and others proposed a fault diagnosis method of micro motor based on sound signal. According to the characteristics of high signal-to-noise ratio and easy to be affected by the environment, the method of maximum correlation kurtosis deconvolution wavelet threshold denoising is used to enhance the periodic impact components in the sound signal and filter out the environmental noise [2]. The envelope and envelope spectrum of the signal are obtained by Hilbert transform. According to the shape of the envelope and the frequency corresponding to the peak value of the envelope spectrum, the fault diagnosis of micro motor is realized. Based on the idea of multi-source information fusion, Zhang Yahui and others adopted the fusion correlation spectrum characteristics of motor stator current and vibration signal as the diagnosis basis of rotor broken bar and stator turn to turn short circuit fault [3]. By fusing the characteristic signals containing the same fault frequency component for correlation analysis and establishing the correlation relationship between different signals, they can effectively suppress the spectrum components not related to fault identification in the single signal spectrum, make the motor fault characteristic frequency component more prominent and reduce the difficulty of fault identification. The fast separation method of motor fault signal can keep the motor itself in good operation condition, but there is still the problem of interaction between multi-component signal separation and feature extraction of non-stationary signal. Motor and its related power equipment are important assets of enterprises. Its reliability and stability in the operation process is the key to ensure the safe and stable operation of mechanical equipment for a long time.

Therefore, it is necessary to study the fast separation method of motor fault signal. Wavelet analysis is a kind of time-frequency analysis, which is developed on the basis of Fourier analysis. It decomposes the signal into the superposition of a series of wavelet functions. Because wavelet transform is a local transformation of signal time-frequency domain, it eliminates the influence of signal redundant information and can extract feature information more effectively. The high-frequency coefficient matrix of each layer of wavelet transform is formed into a sequence related to probability distribution, and its entropy value can be obtained through calculation, which is the representation of the average complexity of wavelet coefficient distribution. Wavelet entropy contains a lot of information that can characterize the fault characteristics. According to the change of wavelet entropy before and after motor fault, the motor state is detected. In this paper, a fast separation method of motor fault signals based on wavelet entropy is proposed. The method first collects the vibration signal of the motor equipment fault, and by estimating the bandwidth of the modal, it is converted into the frequency domain and solved to obtain the motor fault vibration signal to be processed. Then, the noise reduction process is carried out. Based on the feature extraction of the motor fault signal by the wavelet entropy, a rapid separation model of the motor fault signal is established to realize the rapid separation of the fault signal. Finally, experiments are used to prove the advanced nature of this method. The method can improve the accuracy of motor fault diagnosis, has certain practical significance for ensuring the safe production of motors, and can also provide reference for signal separation in related fields.

2 Fast Separation Method of Motor Fault Signal Based on Wavelet Entropy

2.1 Obtain Motor Fault Vibration Signal

Vibration signal is one of the direct feedback of motor dynamic behavior, which contains the characteristics and attributes that can accurately describe the motor fault state. Because the motor vibration signal presents the characteristics of non-stationary and non-linear, and the vibration signal in fault state is quite different from the normal state, it can reflect the characteristics of different motor fault states [4]. In this paper, the vibration signal of motor is obtained by modal decomposition. The flow of modal decomposition is shown in Fig. 1.

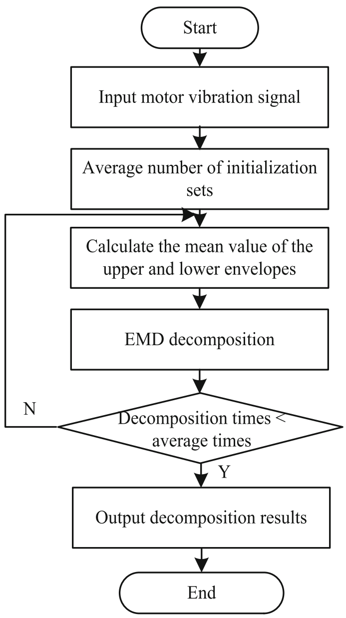

Fig. 1. Flow of modal decomposition

Modal decomposition finds the maximum and minimum values of the motor signal, connects these extreme points in the form of spline interpolation as the upper and lower envelope of the signal, and removes the arithmetic mean of the envelope as the low-pass baseline component. The remaining high-frequency oscillation part is the mode of the motor signal. After modal decomposition, the original motor signal can be expressed as:

$$\beta(t) = \sum_{a=1}^{b} \chi_a(t) + \delta_b(t) \tag{1}$$

In formula (1), t represents time; $\beta(t)$ is the mode of the original motor signal; $\chi_a(t)$ is each IMF component; $\delta_b(t)$ is the residual component; a is the number of components; b is the mean value of the upper and lower envelope. Hilbert transform the mode to obtain its unilateral spectrum. The calculation formula is as follows:

$$f(t) = \left[\alpha(t) + \frac{\lambda}{\pi t}\right] * \beta(t) \tag{2}$$

In formula (2), $f(t)$ represents the single side spectrum of motor fault vibration signal; $\alpha(t)$ is the unit impulse function; λ is imaginary unit; $*$ stands for convolution. Then, the frequency spectrum of the mode is moved to the corresponding fundamental frequency band. By estimating the bandwidth of the mode, the motor fault vibration signal is converted to the frequency domain for solution, and the motor fault vibration signal to be processed is obtained.

2.2 Noise Reduction Processing of Motor Fault Vibration Signal

In addition to rich fault characteristic information, the vibration signal generated by the motor in case of fault usually includes other interference noise. Therefore, it is necessary to denoise the obtained motor fault vibration signal. Wavelet transform can work in time domain or frequency domain, and extract the local information through the analysis of the signal [5]. In this paper, wavelet soft threshold is used to denoise the motor fault vibration signal. A one-dimensional signal model with noise can be expressed as:

$$B(t) = G(t) + \kappa(t) \tag{3}$$

In formula (3), $B(t)$ represents a one-dimensional signal with noise; $G(t)$ is the $\frac{1}{\vartheta}$ noise signal to be extracted, and ϑ is the frequency; $\kappa(t)$ is the background noise signal of the environment and system in the detection process. For the processing of the same signal, the results may vary greatly after using different wavelet functions to transform the signal. Therefore, when processing and analyzing the signal in practical application, we should consider the characteristics of the analyzed signal and the adaptability of the wavelet function, and select the wavelet function that can well reflect the characteristics of the signal. In engineering signal analysis, DB4 shows good performance in frequency domain. Therefore, DB4 wavelet is selected as the wavelet function in this paper. The orthogonal wavelet basis DB4 is selected on MATLAB software, and the wavelet packet coefficients of different frequency bands are obtained by using wpdec function and wpcoef function to decompose and solve the wavelet packet coefficients of each frequency band. After 3-layer wavelet packet decomposition, the signal is also decomposed into the average adjacent subbands by wavelet packet, that is, there will be 8 subbands. After wavelet decomposition, in order to separate the signal from the noise, it is necessary to select an appropriate number as the threshold. When the calculated decomposition coefficient is less than the selected threshold, the decomposition coefficient can be regarded as caused by noise and discarded; On the contrary, it is considered to be mainly caused by signals [6]. According to the principle of wavelet packet energy spectrum analysis, the percentage of each frequency band in the total signal energy can be obtained by dividing the energy of each channel after wavelet packet decomposition by the total signal energy. At this time, the setting method of soft threshold is adopted, which shrinks a fixed value to zero, and then reconstructs the wavelet coefficients after wavelet decomposition through the formula. The soft threshold function mentioned here is:

$$p' = \begin{cases} \operatorname{sgn} p(|p| - \varphi), & |p| \geq \varphi \\ 0, & |p| < \varphi \end{cases} \tag{4}$$

In Eq. (4), p' is the high-frequency wavelet coefficient obtained by operation; sgn is a symbolic function; p the appropriate number selected from the high-frequency wavelet coefficients; φ represents the threshold. Through this capability spectrum analysis, we can roughly know the approximate frequency range of the fault point. After the motor fault vibration signal is decomposed by wavelet packet, because the number and width of samples in each frequency band are equal, the energy spectrum obtained by wavelet packet decomposition can be transformed into histogram, which is convenient and intuitive to observe the feature quantity.

2.3 Feature Extraction of Motor Fault Signal Based on Wavelet Entropy

In the research process, this paper will find out the relevant features in turn, focus on wavelet entropy, set sliding window for simulation, select the best features for extraction, and set parameters for comparison. Because this signal has great difference in frequency distribution, and wavelet analysis has good localization characteristics in frequency domain. Compared with wavelet transform, the high-frequency part of the signal shows better frequency resolution and can show the characteristics contained in the high-frequency part of the signal. Therefore, this paper mainly starts with the two calculation methods of spectrum entropy and energy entropy. The analysis flow of extracting motor fault signal characteristics based on wavelet entropy is shown in Fig. 2.

When the motor fails, the voltage and current on the line will suddenly change. Because the line adopts distributed parameters in this paper, the sudden change signal will make the fault voltage and current signals reflect back and forth continuously, resulting in the waveform distortion of fault voltage or current in the transient process. The calculation of spectral entropy is mainly aimed at the frequency spectrum. After the frequency spectrum of the signal is made by Fourier transform, for the frequency distribution, the amplitude of each frequency point is taken as the sum of squares, and then the square of the amplitude of each point is divided by the total sum of squares to obtain

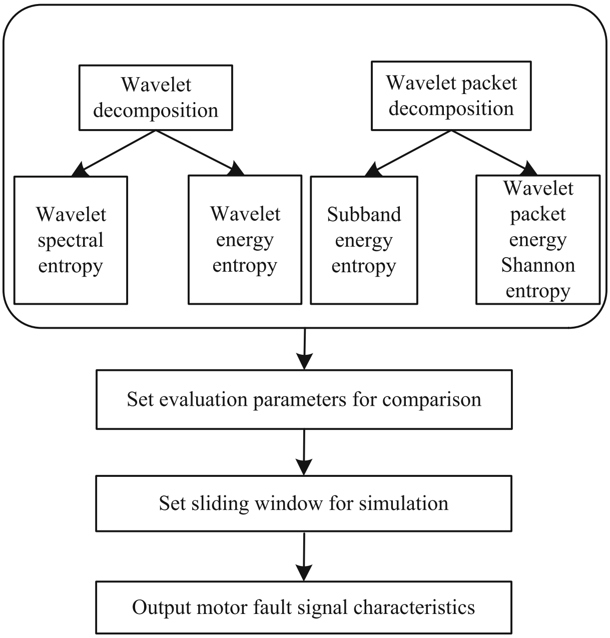

Fig. 2. Analysis flow of extracting motor fault signal characteristics based on wavelet entropy

the probability, that is, the probability of frequency distribution [7]. Relative entropy can be used as a measure of the difference between two signals. When the difference between two signals is large, the relative entropy between signals will show a larger value. When the similarity between two signals is large, the relative entropy between signals will show a smaller value. The calculation formula of frequency distribution probability is as follows:

$$q_x = \frac{A_x^2}{\sum_c A_x^2} \tag{5}$$

In formula (5), q_x represents the probability of frequency distribution; A_x represents the amplitude of each frequency point; x and c represent the serial number and total number of frequency points. The spectrum entropy can be further calculated, and the formula is as follows:

$$H = -\sum_c q_x \log q_x \tag{6}$$

In Eq. (6), H represents the spectral entropy. Therefore, combined with wavelet packet transform and relative entropy, a comprehensive wavelet entropy which can quantify the difference between a fault point and other signal points in motor operation is constructed. If the fault signal is decomposed by wavelet multi-layer decomposition, the order of singular value greater than 0 may be very large after singular value decomposition and transformation. Therefore, wavelet entropy can quantitatively describe the time-frequency and energy distribution of motor fault transient vibration signal. The calculation of energy entropy is mainly aimed at the energy proportion of each frequency band. After wavelet decomposition or wavelet packet decomposition, the signal is decomposed to each subband. Firstly, the sum of squares of all reconstruction coefficients on each node should be calculated, that is, the energy value of each subband. By calculating the energy proportion of each subband, the energy entropy can be obtained. There are many high-frequency components in the transient components of the voltage or current signal of the fault phase, and the non fault signal fluctuates near the fundamental frequency, so the spatial arrangement of the fault phase voltage and non fault phase voltage signal in time domain and frequency domain is different [8]. By comparing the relative difference of wavelet entropy between fault phase and non fault phase, the motor fault signal is identified.

2.4 The Fast Separation Model of Motor Fault Signal is Established

Based on the feature extraction of motor fault signal by wavelet entropy, a fast separation model of motor fault signal is established. Taking full advantage of the characteristics of instantaneous frequency estimation of each component of the signal, a non-stationary multi-component motor fault signal separation method is formed, which successfully solves the two key problems of multi-component signal separation and feature extraction of non-stationary signal in signal processing. The singular points of the signal can be divided into two categories. One is that the amplitude of the signal changes suddenly at a certain time, resulting in the discontinuity of the signal; The other is that the amplitude waveform of the signal is continuous, but its first-order differential is discontinuous. By means of frequency domain filtering, the signal decomposition problem is transformed into a constrained optimization problem. Its ultimate goal is to decompose the real signal with multiple frequency components into a series of discrete quasi orthogonal sub signals, that is, the finite bandwidth eigenmode function, and minimize the sum of the limited bandwidth of all modes [9]. In this paper, if estimation is used as the reference instantaneous frequency parameter of each component, and second-order VKF filter is selected to extract multiple components at the same time, so as to realize the separation of multi-component signals. Each mode has its own center frequency, which can be regarded as tightly supported in the spectrum. The set of all modes is the optimal reconstruction of the original signal. The time-frequency baseline extracted by the instantaneous frequency estimation method can estimate the instantaneous frequency of the signal component of interest to obtain its carrier matrix. Then the reconstruction form of each component signal is:

$$U = WZ \tag{7}$$

In Eq. (7), U represents the reconstruction form of each component signal; W represents the amplitude envelope of the component; Z represents carrier matrix. In case of motor fault, the signal traveling wave generated from the fault will always exist, refraction and reflection will occur at the same time, and the traveling wave will not disappear until the motor fault signal is cut off or restored to normal. On the basis of fully considering the narrowband characteristics of the signal, the optimal Wiener filter is constructed adaptively according to the center frequency of the mode, which makes the frequency band of the mode more concentrated and the signal-to-noise ratio higher. The components realizing signal separation still belong to non-stationary signals, and order analysis can transform the signal from non-stationary in time domain to stationary in angle domain through equal angle resampling [10]. The order ratio (order) is defined as the number of cyclic vibrations of the object to be measured for each revolution. The expression is:

$$\varpi = \frac{\eta\varsigma}{v} \tag{8}$$

In formula (8), ϖ represents the order; η represents vibration frequency; v represents the speed; ς indicates the frequency of motor rotation. Carry out diagonal slice bispectrum analysis on the signal residue. When the input speed is unique, the order diagonal slice bispectrum analysis based on speed can be carried out to extract the amplitude frequency characteristics of the signal residue. Using the interval estimation method, for the collected sample data of similar faults, the value interval of wavelet entropy at each level in the population with sufficient confidence can be estimated from the sample data, that is, the confidence interval. When the wavelet entropy of each scale is within the confidence interval determined by the sample, this kind of fault can be explained. Finally, the instantaneous frequency estimation and order amplitude characteristics and the amplitude frequency characteristics of diagonal slice bispectrum are used to diagnose the vibration signal. Based on the above process, the design of motor fault signal fast separation method based on wavelet entropy is completed.

3 Experimental Analysis

3.1 Experimental Preparation

The motor vibration data used in this experiment are collected by sqi-mfs mechanical fault. In the process of data acquisition, the speed of the motor is controlled by the frequency converter to obtain the vibration data of the motor at different speeds. The frequency conversion meter can display the current speed and corresponding frequency. The acceleration sensor is horizontally installed above the driving end and load end of the motor to collect motor vibration signals in different states. The motor status can be described as normal, broken rotor bar, bearing fault, stator winding and voltage imbalance. 150 samples are collected for each motor state, and the training set and test set are divided according to the ratio of 4:1. The sampling frequency of the experiment is 128 Hz and the motor speed is 1600 rpm. The fast separation methods of motor fault signals based on 1d-cnn algorithm, sound signal and fusion correlation spectrum are selected as the control group, and compared with the design method in this paper. In order to better compare and evaluate the performance of this method and other improved methods for motor fault signal separation and extraction, this paper uses the fault characteristic coefficient as the quantitative index. This index can be expressed as the ratio of the amplitude of the fault characteristic frequency component of the signal to the amplitude of all frequency components. The fault characteristic coefficient is regarded as the ratio of fault component energy to total signal energy in the signal. The larger its value is, the higher the proportion of fault component energy is, indicating that the more obvious the fault characteristic is, and the more effective the fault signal separation is.

3.2 Results and Analysis

In order to fully verify the advanced nature of the method in this paper, Fast separation method of motor fault signal based on 1d-cnn algorithm is selected as comparison method 1, Fast separation method of motor fault signal based on sound signal as comparison method 2 and Fast separation method of motor fault Signal based on fusion correlation spectrum is the comparison method 3, and a comparison experiment is carried out with the method in this paper. The separation effect of the motor fault signal is related to the noise intensity, so this paper conducts experimental tests under different noise intensity conditions, and the results are shown in Figs. 3, 4, 5 and 6.

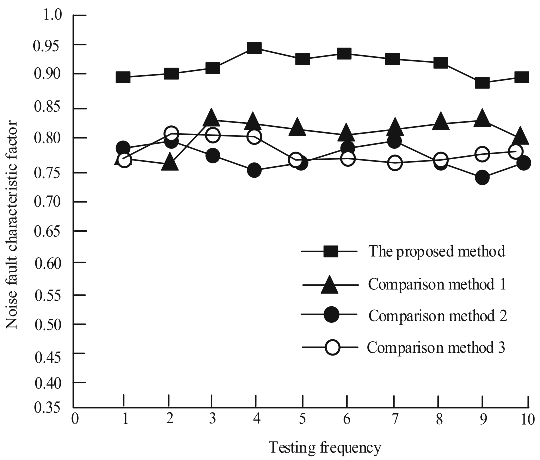

Fig. 3. Fault characteristic coefficient of noise = 0 dB

In the case of noise = 0 dB, after multiple tests, the fault characteristic coefficient obtained by the proposed method is in the range of 0.883–0.942, and the average fault characteristic coefficient is 0.919, which are all better than the comparison method. Compared with method 3, the improvement is 0.150, 0.118 and 0.144.

In the case of noise = 1 dB, after multiple tests, the fault characteristic coefficient obtained by the proposed method is in the range of 0.848–0.886, and the average fault characteristic coefficient is 0.867, which are all better than the comparison method. Compared with method 3, the improvement is 0.149, 0.163 and 0.166.

In the case of noise = 1 dB, after multiple tests, the fault characteristic coefficient obtained by the proposed method is in the range of 0.741–0.786, and the average fault characteristic coefficient is 0.764, which are all better than the comparison method. Compared with method 3, the improvement is 0.143, 0.146 and 0.152.

In the case of noise = 4 dB, after multiple tests, the fault characteristic coefficient obtained by the proposed method is in the range of 0.668 – 0.723, and the average

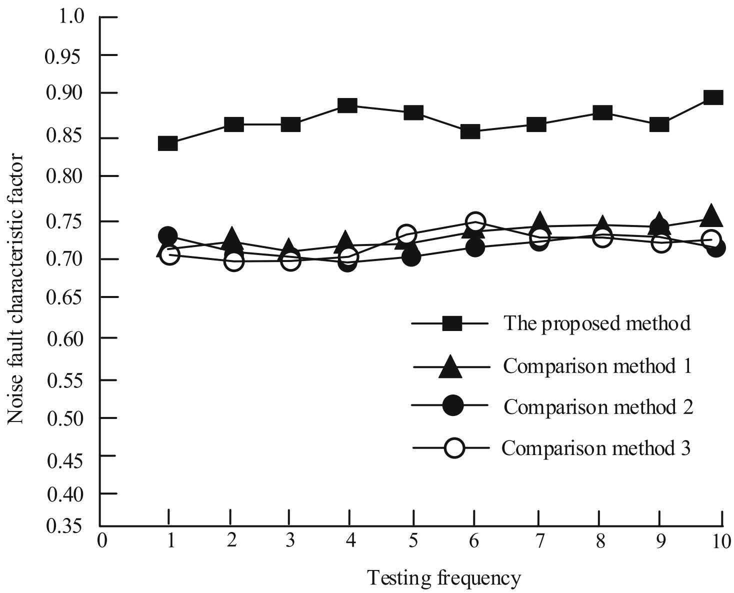

Fig. 4. Fault characteristic coefficient of noise = 1 dB

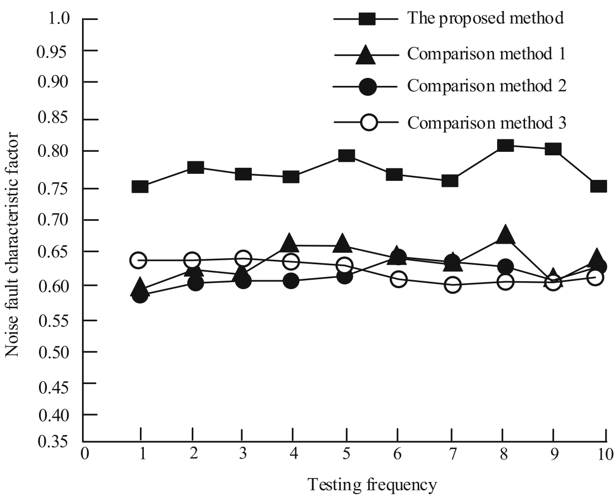

Fig. 5. Fault characteristic coefficient of noise = 2 dB

fault characteristic coefficient is 0.687, which are all better than the comparison method. Compared with method 3, the improvement is 0.191, 0.195 and 0.227.With the increase of noise intensity, the time-frequency baseline of motor signal becomes more and more blurred, and the dispersion of signal peak points increases, which increases the difficulty of fault signal separation. The method based on wavelet entropy can still effectively

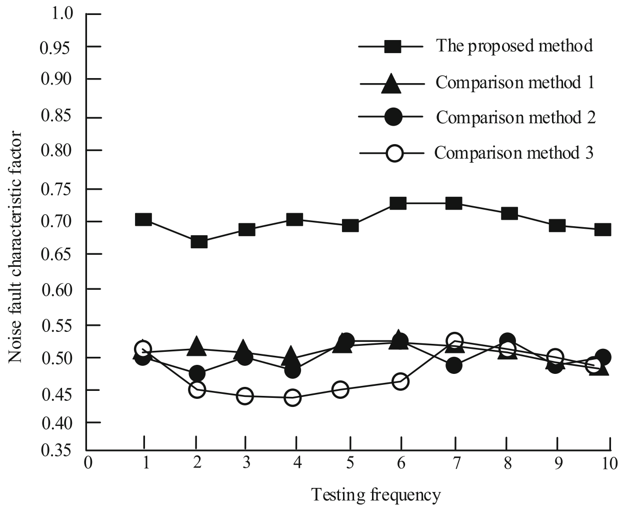

Fig. 6. Fault characteristic coefficient of noise = 4 dB

extract motor fault features when the noise intensity increases, realize the rapid separation of fault signals, and show an ideal separation effect.

4 Concluding Remarks

As a widely used power output equipment, motor plays an important role in many fields such as industry, agriculture and transportation, which is directly related to the production efficiency and operation reliability of the whole system. Therefore, motor fault signal diagnosis technology has important research value and significance. In this paper, a fast separation method of motor fault signal is proposed based on wavelet entropy. This method can realize the effective separation and extraction of motor fault signal, and can also achieve good results under high noise intensity. In this paper, wavelet spectrum entropy and energy entropy are used as fault feature quantities for classification and recognition, but the size of wavelet entropy is closely related to decomposition wavelet and decomposition scale. Therefore, selecting a reasonable wavelet and decomposition scale is a very complex problem. In the future, we will continue to try and follow up on this problem in order to achieve better results.

Fund Project. Hunan Provincial Department of Education Youth Fund Project (21B0690); Shaoyang City Science and Technology Plan Project (2021GZ039); Hunan Provincial Science and Technology Department Science and Technology Plan Project (2016TP1023)

References

1. Wang, X., Mao, D.-X., Li, X.-D.: Motor fault diagnosis using microphones and one-dimensional convolutional neural network. Noise Vib. Control **41**(2), 125–129 (2021)
2. Cai, W.-W., Huang, J., Li, W.-G., et al.: Research on fault diagnosis method for micro motor based on sound signal. Mach. Tool Hydraulics **48**(23), 190–195 (2020)
3. Zhang, Y.-H., Yang, K., Li, T.-L.: Fault diagnosis method of asynchronous motors using fusion correlation spectrum. Electric Mach. Control **25**(11), 1–7 (2021)
4. Wang, D.-M.: Sparse decomposition based maintenance simulation of mechanical and electrical faults of aviation equipment. Comput. Simul. **38**(1), 37–41 (2021)
5. Shen, H.-F., Shi, J.: Fault feature extraction method of motor rotor vibration signals. Noise Vib. Control, **42**(04), 138–143+151 (2022)
6. Wang, C.-L., Lu, X.-J.: A motor bearing fault diagnosis based on deep learning method. J. Lanzhou Jiaotong Univ. **39**(2), 43–50 (2020)
7. Zhao, S.T., Wang, E.X., Chen, X.-X., et al.: Fault diagnosis method for large motor based on sound-vibration signal combined with 1D-CNN. J. Harbin Inst. Technol. **52**(09), 116–122 (2020)
8. Zhang, Y.H., Wang, Y.-F., Zhao, X.-P., et al.: Motor fault diagnosis based on deep metric learning. Measur. Control Technol. **39**(7), 30–37 (2020)
9. Wang, B., Ding, J.-H., Sheng, G.: Design of host computer for vibration signal acquisition of motor fault monitoring system. Autom. Instrum. **36**(02), 11–15 (2021)
10. Yan, J.-L.: Motor fault diagnosis method based on vibration analysis. Appl. IC **38**(7), 88–89 (2021)