Research Article

A New Fault Diagnosis Method for Rotating Machinery Based on SCA-FastICA

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When the rotary machinery is running, the vibration signals measured with sensors are mixed with all vibration sources and contain very strong noises. It is difficult to separate mixed signals with conventional methods of signal processing, so there are difficulties in machine health monitoring and fault diagnosis. The principle and method of blind source separation were introduced, and it was pointed out that the blind source separation algorithm was invalid in strong pulse noise environment. In these environments, the vibration signals are first denoised with the synchronous cumulative average noise reduction (SCA) method, and the denoised signals were separated with the improved fast independent component analysis (FastICA) algorithm. The results of simulation test and rotor fault experiments demonstrate that the novel method can effectively extract fault features, certifying its superiority in comparison with previous methods. Therefore, it is likely to be useful and practical in the fault detection area, especially under the condition of strong noise and vibration interferences.

1. Introduction

During the operation of rotating machinery, the vibration signal measured by the sensor is usually superimposed by the vibration of multiple components [1–3]. How to analyze, process, and identify these signals is very important for judging the working state of rotating machinery and fault diagnosis of equipment [4]. It is very difficult to analyze and process the sensor signal directly, which is bound to cause great difficulties to the mechanical condition monitoring and fault diagnosis [5].

Various traditional modern signal processing methods, such as empirical mode decomposition (EMD) [6], wavelet transform [7, 8], adaptive filter [9, 10], Kalman filter [11, 12], and mathematical morphology analysis [13, 14], have been widely used in vibration signal analysis. Qin et al. [5] proposed a novel M-band flexible wavelet transform for identifying the underlying fault features in measured signals. Wang et al. [2] proposed a step-by-step compound faults

diagnosis method for equipment based on majorization-minimization (MM) and constraint sparse component analysis (SCA). Lu et al. [15] proposes a novel approach to periodic fault signal enhancement in rotating machine vibrations with a tris table mechanical vibration amplifier (TMVA) by exploiting stochastic resonance (SR). However, the abovementioned analysis methods are obviously inadequate for the vibration signals of multiple overlapped on rotating machinery. The blind source separation technology can realize the separation of multiple aliasing signals, the blind source separation is not affected by the overlapping of time and spectrum of the source signals, and the output signal after separation will not lose the weak characteristic information of the source signal.

So far, there have been many effective and distinctive blind source separation algorithms. Typical algorithms include fast fixed-point algorithm [16], natural gradient algorithm [17], EASI Algorithm [18], and JADE algorithm [19–22]. These algorithms show good separation

performance when separating the noiseless mixed signals [23, 24]. However, when separating noisy signals, there will be a lot of errors, even when the signal-to-noise ratio is low, and a completely wrong conclusion will be drawn because these algorithms are derived without considering the noise model. During the operation of the machine, the vibration signal measured by the vibration sensor inevitably contains noise signal. Therefore, when blind source separation algorithm is used to separate the overlapped vibration signals directly, it may cause great errors or draw wrong conclusions. Therefore, it is very important to reduce noise before blind separation of measured mechanical vibration signals, so as to improve the signal-to-noise ratio. So far, many scholars [25, 26] have used the combination of the wavelet denoising method and blind source separation to realize the separation of aliased signals in the noise environment, but the wavelet denoising method needs to set a wide value, which may remove the weak signals of useful components in the aliased signals, leading to the wrong separation results [25, 27]. The synchronous cumulative average algorithm [28, 29] is based on the characteristic of periodic repetition of vibration signal. It can improve the signal-to-noise ratio through the cumulative average processing of multiple periodic sampling points, without losing weak signal. In order to solve the problem of fault feature extraction of rotating machinery under strong noise, a fault separation method combining synchronous cumulative average noise reduction (SCA) algorithm and improved FastICA algorithm (SCA-FastICA) is proposed. Firstly, accumulated average algorithm is used to reduce the noise of the mixed vibration signals, and then the improved FastICA algorithm is used to separate the noise reduced signals, so as to achieve the extraction of fault feature signals.

2. Blind Source Separation

2.1. The Principle of Blind Source Separation. Blind source separation is one of the most widely used applications in blind signal processing. The so-called blind source separation is the process of separating the source signal from the mixed signal when the source signal and transmission channel are unknown by calculating the separation matrix. The schematic diagram is shown in Figure 1.

Blind source separation algorithm aims to separate independent mixed sources. Assuming that the sources are independent and the signal source is $S(t)$, the observation matrix $X(t)$ can be expressed as [25, 30]

$$X(t) = AS(t), \quad (1)$$

where A is a linear operator. The purpose of blind source separation is to find a linear operator W to reconstruct the source signal, and the reconstructed signal $Y(t)$ is [19, 31]

$$Y(t) = WX(t). \quad (2)$$

When W is the inverse of A , it is the most ideal state. In this case, due to the lack of prior knowledge of the source signal, there is uncertainty expansion factor, which can only meet the following requirements in general:

FIGURE 1: Principle of blind source separation.

$$WA = PD, \quad (3)$$

where P is the permutation matrix and D is the diagonal matrix. Through the abovementioned analysis, we can see that the blind source separation problem cannot guarantee the uniqueness of the solution, and the separated signals have major differences in amplitude, phase, and sequence. Although the separated signal lacks the prior knowledge due to the unknown parameter information of the signal source and the characteristics of the transmission channel, the separated signal waveform is still consistent with the corresponding source signal.

2.2. Model of Blind Source Separation with Noise. The vibration signals of n sources can be expressed as $s(t) = (s_1(t), s_2(t), \dots, s_n(t))^T \in R^{n \times T_0}$, T_0 represents the number of signal sampling points, n source signals in the process of transmission and reception due to signal aliasing, and the received mixed signals are expressed as $x(t) = (x_1(t), x_2(t), \dots, x_m(t))^T \in R^{m \times T_0}$, m is the number of receiving sensors. The mathematical model of BSS with noise is expressed as

$$x(t) = As(t) + n(t), \quad (4)$$

where $A = (a_{ij})$ is a mixed matrix of $m \times n$; $n(t) = (n_1(t), n_2(t), \dots, n_m(t))^T \in R^{m \times T_0}$, $n(t)$ indicates that there are m additive noises in the received signal. Because the blind source separation algorithm is very sensitive to noise, the presence of noise reduces the signal-to-noise ratio, which makes the separation effect seriously worse.

3. Blind Source Separation of Multifault Vibration Signals Based on SCA-FastICA

3.1. FastICA Algorithm. In FastICA algorithm based on negative entropy maximization, the expression of negative entropy of random variable is defined as

$$J(x) = H(x_g) - H(x), \quad (5)$$

where x_g is a Gaussian random variable with the same covariance as the random variable x .

Because the prior knowledge of signal is limited and the probability density function of random variable is unknown, when solving ICA problem, formula (5) cannot be used directly, so high-order cumulant is usually used to approximate the probability density function of signal, and then the approximate expression of negative entropy is

$$J(x) \propto \{E[G(x)] - E[G(x_g)]\}^2, \quad (6)$$

where $G(\cdot)$ is a nonlinear quadratic function.

The essence of FastICA algorithm is to select a suitable transformation matrix W to maximize the value of negative entropy $J(W^T x)$. Because when the mean value is 0 and the variance is 1, solving the maximum value of $J(W^T x)$ can be equivalent to finding the maximum value of $E(GW^T x)$. Therefore, before the algorithm starts, two steps of centralization and whitening are needed to preprocess, so that the problem can be transformed to meet the requirements of $E(GW^T x) = \|W\|^2 = 1$. Then, the maximum value of $E(GW^T x)$ is obtained. Using the Newton method to calculate and simplify, the iterative formula can be obtained as follows:

$$W_{k+1} = E\{xg(W_k^T x) - E\{g'(W_k^T x)\}W_k\}. \quad (7)$$

Normalization can be expressed as

$$W_{k+1} = \frac{W_{k+1}}{\|W_{k+1}\|}, \quad (8)$$

where $g(\cdot)$ is the first derivative of $G(\cdot)$; $g'(\cdot)$ is the second derivative of $G(\cdot)$.

$G(\cdot)$ has several common expressions, which can be expressed as

$$\begin{aligned} G(x) &= -\exp\left(-\frac{x^2}{2}\right), \\ g(x) &= x \exp\left(-\frac{x^2}{2}\right), \\ g'(x) &= (1-x)^2 \exp\left(-\frac{x^2}{2}\right). \end{aligned} \quad (9)$$

It can be seen that in the iterative operation that because only one independent component can be separated from each iteration, if you want to extract multiple independent components, you need to carry out multiple iterations. To ensure that each extracted component is a new one, you can carry out the decomposition method of Schmidt orthogonalization after each iteration, so as to achieve the effect of removing the separated variables.

According to the abovementioned analysis, the steps of FastICA algorithm are as follows:

- (1) Preprocessing of observation signal: centralized and whitened to get the observation signal with the mean value of 0 and no correlation
- (2) Let m be the total number of separated signals, and let p be 1
- (3) Randomly select W_p , and initialize $W_p = W_p / \|W_p\|$
- (4) Update W_p , and make

$$W_{p+1} = E\{xg(W_p^T x) - E\{g'(W_p^T x)\}W_p\}. \quad (10)$$

- (5) Orthogonalize W_p by formula $W_p(k+1) = W_p(k+1) - \sum_{i=1}^{p-1} (W_p^T(k+1)W_i)W_i$
- (6) Normalize W_p by the formula $W_p = W_p / \|W_p\|$

(7) In the convergence and divergence analysis of W_p , if it converges, it will go to step 4, otherwise it will go to the next step

(8) Let $p = p + 1$ and if not greater than m , go to step 3, otherwise separate an independent component, and the algorithm ends

3.2. Synchronous Accumulation Average Algorithm. Let the input signal $y(t)$ be a mixed signal formed by the source signal and noise, and the mathematical form can be expressed as

$$y(t) = s(t) + n(t), \quad (11)$$

where $s(t)$ is a useful periodic signal; $n(t)$ is a noise signal. If the starting sampling time is t_k and the sampling period is T , the signal of the i th sampling point is

$$y(t_k + iT) = s(t_k + iT) + n(t_k + iT), \quad (12)$$

where i is the number of sampling sequences.

For the periodic signal $s(t)$, for different sampling periods in the synchronous state, t_k time has the same sampling value. Therefore,

$$s(t_k + iT) = s(t_k). \quad (13)$$

After q repeated sampling, the accumulated value of the i th sampling data is

$$\sum_{i=1}^q y(t_k + iT) = \sum_{i=1}^q s(t_k + iT) + \sum_{i=1}^q n(t_k + iT). \quad (14)$$

Signal after q times accumulation is

$$\sum_{i=1}^q s(t_k + iT) = qs(t_k). \quad (15)$$

Noise accumulated by q times according to statistical average is

$$\sum_{i=1}^q n(t_k + iT) = \sqrt{n_1^2(t_k + T) + n_1^2(t_k + 2T) + \dots + n_q^2(t_k + qT)}. \quad (16)$$

Set the average effective value of each sampling noise as $\bar{n}(t)$, after q sampling:

$$\sum_{i=1}^q n(t_k + iT) = \sqrt{q[\bar{n}(t)]^2} = \sqrt{q} \times \bar{n}(t). \quad (17)$$

Then, the SNR after q times accumulation is

$$\text{SNR}_{\text{out}} = \frac{S}{N} = \frac{qs(t_k)}{\sqrt{q} \times \bar{n}(t)} = \sqrt{q} \times \left(\frac{S}{N}\right)_{\text{in}}, \quad (18)$$

where S is a useful periodic signal and N is a noise signal.

It can be seen from equation (18) that, after q -sampling and accumulation of the signal, the signal-to-noise ratio of the input signal will be increased, and the signal-to-noise ratio of the input signal will be proportional to the square root of the accumulation times. Therefore, it can be concluded that when the accumulation times are large enough, the useful signals in the strong noise can be extracted, so as to improve the signal-to-noise ratio. Also, the more the times of accumulation, the better the effect of improvement. Therefore, this paper introduces this algorithm combined with FastICA algorithm, so that the signal sorting can still be completed under the condition of low SNR. At the same time, in order to reduce the adverse factors caused by noise interference, equalization and smoothing are added in the process of signal preprocessing, and convolution and smoothing are carried out after processing the input signal to get the training sequence, so as to further improve the SNR.

3.3. Basic Steps of the SCA-FastICA Method. According to the abovementioned analysis, this paper proposes a comprehensive sorting algorithm, aiming at the disadvantage that FastICA algorithm is sensitive to noise impact and cannot sort low SNR noisy signals, the FastICA algorithm is optimized. The specific algorithm steps are as follows:

- (1) The observed signal is a low SNR signal $s(t)$, the model of blind source separation with noise is established, and the signal is processed by q times accumulation
- (2) Update the input signal $s(t)$, and calculate the effective mean value of the noisy signal, $\bar{y}(t) = \bar{s}(t) + \bar{n}(t)$
- (3) The signal is balanced and smoothed
- (4) FastICA is used to separate blind source signals
- (5) Smooth the separated signal, and observe the separation result

3.4. Similarity Coefficient. The similarity coefficient refers to the degree of consistency between the source signal and the separated signal. In order to facilitate comparison and avoid the influence of reverse phase, the absolute value of the similarity coefficient is generally taken. The calculation formula is [32]

$$\xi_{ij} = \zeta(s_i, y_j) = \frac{\left| \sum_{i=1}^M s_i(t) y_j(t) \right|}{\sqrt{\sum_{i=1}^M s_i^2(t) y_j^2(t)}}, \quad (19)$$

where $s_i(t)$ is the i th component of the signal source and $y_j(t)$ is the j th component corresponding to $s_i(t)$ after separation; $i, j = 1, 2, \dots, N$. It can be seen that the closer the correlation coefficient is to 1, the higher the consistency between the separated signal and the source signal is and the better the separation effect of the algorithm is. When the correlation coefficient is 1, the separation effect is obviously the best.

4. Simulations

In order to verify the algorithm proposed in this paper, four typical signals, $s_1(t), s_2(t), s_3(t), s_4(t)$, are simulated for aliasing separation. The simulation signals are as follows:

$$\begin{cases} s_1(t) = \sin(300\pi t), \\ s_2(t) = \text{sign}[\cos(100\pi t)], \\ s_3(t) = \cos(200\pi t)\sin(300\pi t), \\ s_4(t) = [(\text{mod}(t, 23) - 11)/9]^5. \end{cases} \quad (20)$$

Random noise is added, and FastICA algorithm is used to separate the observation signals with signal-to-noise ratio of 40 dB, 20 dB, and 5 dB. The separation results are shown in Figures 2–4. Figure 5 is the original observation signal. The similarity coefficient analysis is carried out at 40 dB, 5 dB, and 0 dB, as shown in Table 1.

By observing the waveform of simulation results, it can be seen that FastICA algorithm can separate signals well when the SNR is greater than 20 dB. When the SNR is less than 20 dB, the separation effect is significantly reduced. It can be seen that the algorithm is very sensitive to noise impact. When the SNR is 5 dB, it can be seen that the algorithm has completely failed, and the separation fails. Through similarity coefficient analysis, it can be seen that when the SNR is 40 dB, the similarity can reach 1.0, which has a high similarity. Although blind source separation has disorder, it does not affect the discrimination of the separated signal. However, at the low SNR of 5 dB, the algorithm has failed from the waveform, and although it still has a certain similarity, the similarity is significantly reduced. When the SNR is 0 dB, the similarity coefficient can be seen to be reduced to 0.5, which shows that the algorithm has failed at the low SNR. Therefore, it is proved that FastICA algorithm cannot complete signal separation in low SNR.

Separation algorithm proposed in this paper is used to separate the overlapped signals with a signal-to-noise ratio of 5 dB, 0 dB, and -10 dB. The separation results are shown in Figure 6 to Figure 7, and the similarity coefficient analysis of the separation results is carried out under low signal-to-noise ratio. The results are shown in Table 2.

The simulation results show that the proposed algorithm can separate the overlapped signals at low SNR. In the extreme case of signal-to-noise ratio of -10 dB, separation can be basically completed. However, due to the excessive noise, it is inevitable to produce jitter effect on the separated signal, which makes the separation effect reduced. In the range of SNR from 0 dB to 20 dB, signal sorting can be completed well, which reduces the sensitivity of FastICA algorithm to noise. From the analysis of similarity coefficient, we can see that the algorithm proposed in this paper still has high similarity under the condition of low SNR, and the highest correlation coefficient can reach above 1.0, which proves that the algorithm has good sorting effect.

FIGURE 2: FastICA sorting with SNR of 40 dB. (a) Mixed signal with SNR of 40 dB. (b) FastICA sorting with SNR of 40 dB.

FIGURE 3: FastICA sorting with SNR of 20 dB. (a) Mixed signal with SNR of 20 dB. (b) FastICA sorting with SNR of 20 dB.

FIGURE 4: FastICA sorting with SNR of 5 dB. (a) Mixed signal with SNR of 5 dB. (b) FastICA sorting with SNR of 5 dB.

FIGURE 5: Original observation signal.

TABLE 1: Statistical table of similarity coefficient by the FastICA method.

SNR/dB	Similarity coefficient		
40	0.002	1.000	0.021
	1.000	0.024	0.036
	0.011	0.006	0.999
5	0.044	0.865	0.019
	0.826	0.012	0.029
	0.131	0.062	0.765
0	0.155	0.531	0.132
	0.596	0.132	0.127
	0.046	0.019	0.612

FIGURE 6: SCA-FastICA sorting with an SNR of 5 dB.

By comparing Figures 4(b) and 6, it can be seen that the separation method based on FastICA has more noise components. It indicates that the separation result is not accurate. From the evaluation indexes in Table 1 and Table 2, we can also see that the improved algorithm SCA-FastICA is better than FastICA.

5. Experiments

In order to verify the analysis effect of the SCA-FastICA method, the experiments are carried out on the rotor test bench, as shown in Figure 8. The laboratory rotor system can be used to simulate several typical faults of rotating machinery and collect vibration signals needed for fault diagnosis and research.

FIGURE 7: SCA-FastICA sorting with an SNR of -10 dB.

TABLE 2: Statistical table of similarity coefficient by the SCA-FastICA method.

SNR/dB	Similarity coefficient		
10	0.001	1.000	0.013
	0.999	0.011	0.024
	0.002	0.001	0.999
0	0.012	0.992	0.006
	0.995	0.105	0.083
	0.011	0.006	0.996
-10	0.035	0.932	0.034
	0.942	0.114	0.071
	0.081	0.006	0.899

In the experimental double span rotor system, the front and rear span rotors are supported by sliding bearings, and the coupling between the two rotors and between the rotor and the

FIGURE 8: The two-span rotor-bearing rig.

FIGURE 9: Time-frequency waveforms of the rotor's vibration signals. (a) The time-domain signals. (b) The frequency-domain signals.

motor is flexible. The probe of the eddy current sensor is composed of two perpendicular probes, which are installed near the journal and around the disk with obvious vibration and an easy-to-obtain signal. The single sensor at the end of the

rotor is used to measure the real-time speed of the rotor. In order to satisfy the assumption that the number of sensors is greater than or equal to the number of source signals in blind source separation, four sensors are used in the experiment. The

FIGURE 10: The separated signals by FastICA. (a) The time-domain signals. (b) The frequency-domain signals.

rotating speed of the rotor is about 3kr/min, and the sampling frequency is 5kHz. The four measured sensor signals are shown in Figure 9.

Figure 9 shows the time-frequency signal waveform of the collected signal under the rotor rub impact fault. However, according to the time-domain characteristics, it is found that the real rotor vibration signal is seriously polluted by noise, so the fault characteristics of the rotor system cannot be distinguished. According to the characteristics of frequency domain, the 50 Hz power frequency of rotor can be distinguished by the Y1 signal, but the fault characteristics of the rotor cannot be distinguished.

Figure 10 shows the time-frequency waveform separated directly by the FastICA method. From the time-domain characteristics, it can be seen that the real rotor vibration signal is also seriously polluted by noise, so it is impossible to distinguish the fault characteristics of the

rotor system. However, in the frequency domain, the power frequency of the rotor, 50 Hz, can be distinguished by Y1 and Y2 signals, and the fault features of the rotor cannot be identified, which shows that traditional FastICA algorithm cannot separate the fault features of the rotor system under strong noise.

Figure 11 shows the time-frequency waveform separated by the SCA-FastICA method. It can be seen from the time domain that the strong noise is well-contained and the vibration source signal of the rotor is well separated. In the frequency domain of Figure 12, the power frequency of 50 Hz and the second frequency of 100 Hz of the rotor can be distinguished by Y1 and Y2 signals. Through the frequency domain characteristics of Y1 and Y2, the rotor can be judged to have rub impact fault. It can be seen from Y3 signals in the frequency domain that the frequency is distributed in the whole frequency band and the

FIGURE 11: The separated signals by the SCA-FastICA method. (a) The time-domain signals. (b) The frequency-domain signals.

amplitude is relatively small; the signal shows randomness in the time domain at the same time. Combining these two points, it can be judged that Y3 signals are noise signals. It can be seen from Y4 signals in frequency domain of Figure 12 that the frequency of 50 Hz is highlighted while other frequencies are suppressed. Since the power frequency used in daily life is 50 Hz, it can be determined that the signal is a power frequency signal.

6. Conclusions

In order to solve the problem of fault feature extraction of rotating machinery under strong noise, a fault separation method combining synchronous cumulative average noise reduction (SCA) algorithm and improved FastICA algorithm (SCA-FastICA) is proposed. The conclusions are made as follows:

- (1) Blind separation of the observation signal with strong noise is carried out directly, and the error of the separation result is large, even when the wrong result is obtained
- (2) The synchronous cumulative average noise reduction (SCA) algorithm can effectively remove the noise signal without losing the useful components of the original signal, improve the signal-to-noise ratio, and provide the precondition for the accurate realization of blind separation
- (3) For the measured signal, although the independence assumption of blind source separation is not true strictly, SCA-FastICA algorithm is still effective in the actual vibration signal separation
- (4) The combination of synchronous cumulative average noise reduction (SCA) algorithm and blind source separation algorithm provides a new method for the

FIGURE 12: SCA-FastICA sorting with an SNR of 0 dB.

separation of aliased signals in strong noise environment

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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References

- [1] Y. Qin, J. Zou, B. Tang, Y. Wang, and H. Chen, "Transient feature extraction by the improved orthogonal matching pursuit and K-SVD algorithm with adaptive transient dictionary," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 1, pp. 215–227, 2020.
- [2] Y. Hao, L. Song, B. Ren, H. Wang, and L. Cui, "Step-by-Step compound faults diagnosis method for equipment based on majorization-minimization and constraint SCA," *IEEE/ASME Transactions on Mechatronics*, vol. 24, no. 6, pp. 2477–2487, 2019.
- [3] H. Wang, B. Ren, L. Song, and L. Cui, "A novel weighted sparse representation classification strategy based on dictionary learning for rotating machinery," *IEEE Transactions on Instrumentation and Measurement*, vol. 69, no. 3, pp. 712–720, 2020.
- [4] A. Glowacz, "Fault diagnosis of single-phase induction motor based on acoustic signals," *Mechanical Systems and Signal Processing*, vol. 117, pp. 65–80, 2019.
- [5] Y. Qin, Y. Mao, B. Tang, Y. Wang, and H. Chen, "M-band flexible wavelet transform and its application to the fault diagnosis of planetary gear transmission systems," *Mechanical Systems and Signal Processing*, vol. 134, 2019.
- [6] N. E. Huang, M.-L. Wu, W. Qu, S. R. Long, and S. S. P. Shen, "Applications of Hilbert-Huang transform to non-stationary financial time series analysis," *Applied Stochastic Models in Business and Industry*, vol. 19, no. 3, pp. 245–268, 2003.
- [7] G. Özmen and S. Özşen, "A new denoising method for fMRI based on weighted three-dimensional wavelet transform," *Neural Computing and Applications*, vol. 29, no. 8, pp. 263–276, 2018.
- [8] L. Zhao, Y. Feng, R. Xie, J. Xue, L. Zhang, and Z. Wang, "Amplitude and frequency feature extraction for transformer vibration based on cross-wavelet transform," *Gaodiyuan Jishu/High Voltage Engineering*, vol. 45, no. 2, pp. 505–511, 2019.
- [9] C. Liu, Z. Zhang, and X. Tang, "Sign normalised spline adaptive filtering algorithms against impulsive noise," *Signal Processing*, vol. 148, pp. 234–240, 2018.
- [10] M. A. Z. Raja, N. I. Chaudhary, Z. Ahmed, A. Ur Rehman, and M. S. Aslam, "A novel application of kernel adaptive filtering algorithms for attenuation of noise interferences," *Neural Computing and Applications*, vol. 31, no. 12, pp. 9221–9240, 2019.
- [11] Y. Kang, Z. Shi, H. Zhang, D. Zhen, and F. Gu, "A novel method for the dynamic coefficients identification of journal bearings using Kalman filter," *Sensors*, vol. 20, no. 2, 2020.
- [12] M.-C. Pan, W.-C. Chu, and D.-D. Le, "Adaptive angular-velocity Vold-Kalman filter order tracking - theoretical basis, numerical implementation and parameter investigation," *Mechanical Systems and Signal Processing*, vol. 81, pp. 148–161, 2016.
- [13] Y. Ge and X. Jiang, "Mathematical morphology and deep learning-based approach for bearing fault recognition," *International Journal of Performability Engineering*, vol. 14, no. 5, pp. 995–1003, 2018.
- [14] T. Gong, Y. Yuan, X. Yuan, and X. Wu, "Application of optimized multiscale mathematical morphology for bearing fault diagnosis," *Measurement Science and Technology*, vol. 28, no. 4, 2017.
- [15] S. Lu, Q. He, D. Dai, and F. Kong, "Periodic fault signal enhancement in rotating machine vibrations via stochastic resonance," *Journal of Vibration and Control*, vol. 22, no. 20, pp. 4227–4246, 2016.
- [16] A. Aldhabab and W. B. Mikhael, "Face recognition employing DMWT followed by FastICA," *Circuits, Systems, and Signal Processing*, vol. 37, no. 5, pp. 2045–2073, 2018.
- [17] S. Bhardwaj, S. Raghuraman, and A. Acharyya, "Simplex FastICA: an accelerated and low complex architecture design methodology for n -D FastICA," *IEEE Transactions on Very Large Scale Integration (VLSI) Systems*, vol. 27, no. 5, pp. 1124–1137, 2019.

- [18] J. Lu, W. Cheng, Y. Zi, and Z. He, "Nonlinear blind source separation combining with improved particle swarm optimization," *Hsi-An Chiao Tung Ta Hsueh/Journal of Xi'an Jiaotong University*, vol. 50, no. 6, pp. 15–22, 2016.
- [19] D. G. Fantinato, L. T. Duarte, Y. Deville, R. Attux, C. Jutten, and A. Neves, "A second-order statistics method for blind source separation in post-nonlinear mixtures," *Signal Processing*, vol. 155, pp. 63–72, 2019.
- [20] Q. Guo, G. Ruan, and L. Qi, "A complex-valued mixing matrix estimation algorithm for underdetermined blind source separation," *Circuits, Systems, and Signal Processing*, vol. 37, no. 8, pp. 3206–3226, 2018.
- [21] R. Hao, X. An, and Y. Shi, "Single-channel blind source separation based on EMD and CICA and its application to gearbox multi-fault diagnosis. EMDCICA," *Zhendong Yu Chongji/Journal of Vibration and Shock*, vol. 38, no. 8, pp. 225–231, 2019.
- [22] J. Huang and J. Sun, "Sampling adaptive learning algorithm for mobile blind source separation," *Wireless Communications and Mobile Computing*, vol. 2018, Article ID 5048419, 7 pages, 2018.
- [23] C. Wang, H. Huang, Y. Zhang, and Y. Chen, "Variable learning rate EASI-based adaptive blind source separation in situation of nonstationary source and linear time-varying systems," *Journal of Vibroengineering*, vol. 21, no. 3, pp. 627–638, 2019.
- [24] H. Jun, Y. Chen, Q.-H. Zhang, G. Sun, and Q. Hu, "Blind source separation method for bearing vibration signals," *IEEE Access*, vol. 6, pp. 658–664, 2018.
- [25] Y. Liu, K. Li, and P. Chen, "Fault diagnosis for rolling bearings based on synchrosqueezing wavelet transform," *Zhongguo Jixie Gongcheng/China Mechanical Engineering*, vol. 29, no. 5, pp. 585–590, 2018.
- [26] N. Lu, B. Jiang, X. Meng, and H. Zhao, "Diagnosis, diagnosticability analysis, and test point design for multiple faults based on multisignal modeling and blind source separation," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 50, no. 1, pp. 137–148, 2020.
- [27] G. Bayrak, "Wavelet transform-based fault detection method for hydrogen energy-based distributed generators," *International Journal of Hydrogen Energy*, vol. 43, no. 44, pp. 20293–20308, 2018.
- [28] W. Fu, K. Shao, J. Tan, and K. Wang, "fault diagnosis for rolling bearings based on composite multiscale fine-sorted dispersion entropy and SVM with hybrid mutation SCA-HHO algorithm optimization," *IEEE Access*, vol. 8, pp. 13086–13104, 2020.
- [29] Y. Hao, L. Song, L. Cui, and H. Wang, "A three-dimensional geometric features-based SCA algorithm for compound faults diagnosis," *Measurement*, vol. 134, pp. 480–491, 2019.
- [30] L. Chen, S.-Z. Gan, L.-Y. Zhang, and G.-Y. Wang, "Nonlinear blind source separation algorithm based on spline interpolation and artificial bee colony optimization," *Tongxin Xuebao/Journal on Communications*, vol. 38, no. 7, pp. 36–46, 2017.
- [31] Y. Tian, X. Wang, and Y. Zhou, "Novel single channel blind source separation algorithm based on sparse representation," *Dianzi Yu Xinxi Xuebao/Journal of Electronics and Information Technology*, vol. 39, no. 6, pp. 1371–1378, 2017.
- [32] C.-Z. Hu, Q. Yang, M.-Y. Huang, and W.-J. Yan, "Diagnosis of non-linear mixed multiple faults based on under-determined blind source separation for wind turbine gearbox: simulation, testbed and realistic scenarios," *IET Renewable Power Generation*, vol. 11, no. 11, pp. 1418–1429, 2017.