Bearing Fault Diagnosis Based on State-space Principal Component Tracking Filter algorithm

Tangshao Duan1, Zhiqiang Liao1, Taifu Li2, Haihong Tang1, and Peng Chen1,
1 Graduate School of Environmental Science and Technology, Mie University, Tsu, 514-0001 Japan;
2 School of Electrical Engineering, Chongqing University of Science and Technology, Chongqing, 401331 China;
Corresponding author: Haihong Tang (e-mail: tangyanlihaihong@outlook.com), Taifu Li (e-mail: 228683275@qq.com).

ABSTRACT In order to obtain the high-precision bearing fault diagnosis of different speed under strong background noise, a novel method called state-space principal component tracking filtering (SPCTF) is proposed for fault diagnosis, which can recover the fault information through the sequence of "Prediction – Measurement – Correction - Optimal estimation - Principal component extraction" from the polluted raw signals with noise. Firstly, the switch Kalman filter (SKF) is utilized to establish dynamic filter model for time-series signals. And then, a feature tracking matrix is generated from the principal component features that is extracted from the optimal estimated state matrix of each time in the model. Thirdly, the principal component analysis is used to extract the effective fault feature from the redundant information generated in feature tracking matrix. Finally, the fault characteristic frequency is analyzed with the envelope spectrum to achieve high-precision fault diagnosis of bearing. The proposed method is demonstrated on signals from simulation signals and laboratory tests (several speeds), outperforming those of traditional methods.

INDEX TERMS The switch Kalman filter, feature tracking matrix, state-space principal component tracking filtering, fault feature extraction, bearing fault diagnosis.

I. INTRODUCTION
The fault in rolling bearing (one of the most important components in industrial equipment) causes equipment damage, industrial shutdown, and brings great property losses and even casualties. Therefore, it is urgent need for an effective monitor system that can ensure the high-precision and stable operation of equipment [1, 2]. Vibration signal analysis has been widely used in the fault detection of rolling bearing. However, due to the complex working environment of bearing, the low signal-to-noise ratio (SNR) of vibration signal causes difficulties in fault diagnosis. Effective fault feature extraction methods can overcome the problem of high SNR in bearing signal, and numerous fault feature extraction methods have been proposed in recent years [3], including signal decomposition, signal enhancement and signal filtering.

The signal decomposition method, including wavelet analysis [4,5], empirical mode decomposition (EMD) [6-9], variational mode decomposition (VMD) [10-12], decomposes and reconstructs the signal to reduce the influence of noise and then extracts the fault features according to the mathematical theory [13]. However, there are still some limitations in these methods: (I) Wavelet analysis is not precise when applied into high-frequency decomposition; (II) The edge phenomenon and mode mixing are inevitable in EMD; (III) It is difficult to determine the number of mode in VMD; (IV) Those methods undermine the fault characteristic information to a certain extent when removing the noise. Stochastic resonance method can enhance gain of periodic fault feature signal with noise energy to extract the fault characteristic frequency. However, it is difficult for stochastic resonance method to effectively filter the low-frequency interference [14-16]. Furthermore, the structural parameters of the resonance system also have great influence on the results of fault diagnosis. Signal filtering method including high pass filtering, adaptive filtering [17, 18], fractional filtering [19], and Kalman filtering [20], extract the effective frequency band by analyzing the spectrum signal, and then perform fault diagnosis. Liao [18] and Long [19] demonstrated outperformance of signal filtering method in bearing fault diagnosis through comparison with band-pass filtering and wavelet decomposition. However, it has great dependence on the prior knowledge of bearing fault and it is not conducive to the practical industrial application. Fortunately, Kalman filter [21, 22] is an efficient recursive filtering algorithm, which can estimate and track the state of
the system from a series of incomplete sequences, and complete the filtering of signals and the tracking extraction of fault features. Singleton [21] established a data-based Kalman filter fault diagnosis model by using time domain and time-frequency domain features to track the development of bearing fault feature and these feature is used to train the parameters of the established model. Anger [22] proposed a bearing fault diagnosis method based on the Gaussian degradation model of unscented Kalman filter, which improved the dynamic response speed and anti-interference ability of fault diagnosis. However, a single Kalman model is not enough to describe the dynamical fault degradation process, which reduces the universality of the model [23].

The switch Kalman filter algorithm can establish multiple filter models to better describe the dynamic process of system. In recent years, it is widely used in biomedicine, power systems, life prediction, especially in the field of fault diagnosis. Lim [24] proposed three filter models based on SKF and Bayesian estimation to perform failure prognostic. Although the diagnostic accuracy is improved, the amount of data is increased several times, demand high calculative burden, calling thus for the rapid development regarding model order reduction approaches [25]. Moreover, the data recovery and real-time problem is count for much in the field of fault diagnosis [26].

To address these challenges, this article establishes generative fault diagnosis model based on state-space principal component tracking filtering (SPCTF). The contributions of this article are described as follows.

1) The proposed method has better real-time and dynamics than the traditional filter methods when it innovatively adopt the switch Kalman filter to track optimal estimated state matrix consisted with effective fault information in the process of model updating. Moreover, it effectively reduce the dependence of the treated signal (with various filter methods) that has delay time comparing with the proposed method.

2) The proposed method has a novel mechanism compared with traditional filtering method which directly removes unrelated fault information that maybe useful for the diagnosis. The reason for this contribution is the SKF that establish multiple filter models to better describe the dynamic process of system to save rich and useful information in the optimal estimated state matrix.

3) Moreover, the proposed method has ideal anti-interference ability for time-series signals since of the optimal estimated state matrix that is calculated with the optimal estimates and observations during the model update process based on SKF. Therefore, a feature tracking matrix generated with the principal component analysis is extracted from the optimal estimated state matrix in real-time and dynamical, which has high SNR due to the excellent denoising ability of the proposed method.

4) It is important to consider the influence of the computational burden in the optimal estimated state matrix that is a high-dimensional matrix for the actual fault diagnosis.

The reason is that the dynamic model based on SKF multiplies the amount of data since the advantage (multiple filter models) of the SKF. Therefore, the reduced-order method based on principal components analysis is utilized to extract the effective fault feature from the redundant information for generating a feature tracking matrix, which can effectively reduce data dimensions and improve the computing efficiency of SPCTF.

5) Generalization is an important indicator of the diagnosis when changing the working condition. Therefore, the proposed method is applied to other different speeds at 500, 1000, and 1500 rpm. The result showed the effectiveness and strong generalization in the various conditions, especially in 500rpm (low speed). Moreover, the comparative experiment with envelope and high pass filter is utilized to prove that SPCTF has excellent ability that can effectively extract fault feature from strong noise. Furthermore, the comparative experiment with kalman prove that the SKF has better real-time and dynamics to track the effective fault information in signal. Addition, it is effective to prove the advantage of PCA in order-reduction by comparing with BTA, which can improve the efficiency of SPCTF when applied into fault diagnosis.

II. BACKGROUND AND PRELIMINARIES

A. KALMAN FILTER

Kalman filter is an efficient recursive filtering algorithm, which estimates the system state $X_n$ through the state $Y_n$ measured by the system [27] without relying on a large amount of system data. Define a stochastic system state $X_n$, and then the stochastic difference equation and observation equation of the system can be expressed as:

$$X_n = F_{n,n-1}X_{n-1} + W_n$$

$$Y_n = C_nX_n + V_n$$

where $X_n$ is the state vector of the system at discrete time point $n$; $Y_n$ is the observation vector of discrete time point $n$; The matrix $F_{n,n-1}$ and $C_n$ are state transition matrix and observation matrix, respectively. The vectors $W_n$ and $V_n$ are uncorrelated zero mean Gaussian white noise, $W_n \sim (0, Q_1n)$ and $V_n \sim (0, Q_2n)$. The main process of Kalman filtering is as follows:

State vector prediction equation:

$$\hat{X}_n = F_{n,n-1}X_{n-1}$$

where $X_{n-1}$ is optimal estimation at discrete time point $n - 1$.

State prediction correlation matrix:

$$\hat{P}_n = AP_{n,n-1}^T + Q_1n$$

$$A = F_{n,n-1}P_{n-1}$$

Filter gain:

$$G_n = \hat{P}_nC_n^T[\tau_n]^{-1}$$

$$\tau_n = C_n\hat{P}_nC_n^T + Q_2n$$
Innovation process:
\[ \hat{v}_n = Y_n - C_n \hat{x}_n \] (6)

One-step prediction and error correlation matrix:
\[ \begin{align*}
X_n &= \hat{X}_n + G_n \hat{v}_n \\
P_n &= \hat{P}_n - G_n C_n \hat{P}_n
\end{align*} \] (7)

Kalman filter estimation uses (3) and (4) to obtain prior estimation that is corrected through (5)-(6) to obtain the optimal estimation (7) and corresponding estimation error (8).

Kalman filter estimation uses (3) and (4) to obtain prior estimation that is corrected through (5)-(6) to obtain the optimal estimation (7) and corresponding estimation error (8). And then update the relevant prediction parameters according to the returned estimation error for the discrete time point n+1 system state prediction [28].

Although Kalman filter can use small number of prior samples to predict the system state for removing the system noise. However, the accuracy of Kalman filter estimation will decrease with the increase of estimation step since the degradation of bearing is a dynamic process. Therefore, the switch Kalman filter algorithm is introduced to realize dynamic tracking of bearing fault feature in order to solve the limitation of Kalman filter in bearing fault diagnosis.

B. SWITCH KALMAN FILTER

The switch kalman based on Baysian is shown in Fig. 1. Firstly, the various kalman filter models are established through analyzing various possible states of the system. The probability of each state at each moment is calculated, and then analyzing the most likely state of the system at that moment [23, 24, 29]. The detailed process is as follows:

There are m Kalman filter models to be established for a dynamic system based on Bayesian estimation theory. The model transformation probability:
\[ S_{ij} = \frac{Z_{ij}}{\sum Z_{ij}} \] (9)

where the model switch variable \( S_{ij} \) describes the probability of the model switching from \( S_{ij-1} \) to \( S_{ij} \). \( S_{ij} \) is the probability of the model i in discrete time point n-1. \( Z_{ij} \) is the model transition probability. The weighted state and covariance estimates are:
\[ \begin{align*}
\hat{X}_{i,n-1} &= \sum_{s=1}^{m} S_{si,n-1} X_{s,n-1} \\
\hat{P}_{i,n} &= \sum_{s=1}^{m} S_{si,n} \hat{P}_{s,n} + \hat{V}_{i,n} \end{align*} \] (10)

where \( X_{i,n-1} \) is state vector prediction value of \( i^{th} \) model at discrete time point n-1. \( \hat{P}_{i,n} \) is error correlation matrix of \( i^{th} \) model at discrete time point n-1. And then the Likelihood estimation of each filter model:
\[ L_i = N(\hat{a}_i, 0, \tau_i^2) \]
\[ \hat{a}_i = Y_n - C_n \hat{x}_n \]
\[ \tau_i = C_n C_n^T + Q_2 \] (12)

where \( \hat{a}_i \) is measurement residual, \( \tau_i^2 \) residual covariance. Probability of each model at discrete point n:
\[ S_i^n = \frac{L_i^n \prod_{k=1}^{n-1} S_{ik}^{k-1}}{\sum_{i=1}^{m} L_i^n \prod_{k=1}^{n-1} S_{ik}^{k-1}} \] (13)

Finally the weighted state and covariance estimate update are computed as follows:
\[ \begin{align*}
X_n &= \sum_{i=1}^{m} S_i^n X_{i,n} \\
P_n &= \sum_{i=1}^{m} S_i^n \hat{P}_i^n [X_i^n - X_n] [X_i^n - X_n]^T
\end{align*} \] (14)

C. FEATURE EXTRACTION OF BEARING FAULT

The research shows that a pulse force will be excited when the rolling element rolls over the defect, such as pitting, spalling and scratching. And the pulse force is a broadband signal, which can stimulate the high frequency natural vibration of the bearing system, as shown in Fig. 2.

Recently, the time series modeling autoregressive (AR) model, known as high-resolution parametric spectrum analysis method and great capable of revealing the occurrence of rotating machinery fault, has been applied to vibration signal analysis [30, 31]. Therefore, the AR is utilized to establish an autoregressive state equation for the switched Kalman to obtain the optimal estimated state matrix.

Conduct \( A_n = [a_1(n), a_2(n), \ldots, a_p(n)] \) as the weighted parameter of stochastic difference equation, the estimate \( x_n \) can be described:
\[ x_n = \sum_{k=1}^{m} a_{p} x_{n-p} + e_n \] (15)

where \( e_n \) is the optimal estimation error.

Conduct \( X_n = [x_{n-1}, x_{n-2}, \ldots, x_{n-p}] \) as the input vector (bearing vibration signal) of SKF at discrete time point n, taking into account the characteristics that the optimal parameters will change with iteration, the process noise \( V_n \) is introduced. The expected output of each SKF model \( x_n = X_n A_n + V_n \). Furthermore, \( A_n \) is the key parameter to be estimated in the process of applied SKF into fault diagnosis The state equation and prediction equation is:
\[ A_n = F_n A_{n-1} + W_n, x_n = X_n A_n + V_n \] (16)

According to (1, 2), \( W_n \) and \( V_n \) are uncorrelated zero mean Gaussian white noise, \( W_n \sim (0, Q_1 n) \) and \( V_n \sim (0, Q_2 n) \). Initialize
$F_0$, as the identity matrix, $q = 10^{-6}$ as the variance of $W_0$, thus $Q_1 = qI$, take the variance of $X_1 = [x_1, x_2, \ldots, x_p]$ as $V_1$. The final state vector $A_n$ will converge to its best estimate value through performs multiple iterations and operations on the filter model with (9-14).

SKF can not only effectively remove the interference of noise, but the state vector matrix $A_n$ retain the key fault features of the signal during the update of SKF model. However the $A_n$ will increase the data dimension by $p$ times, thus PCA is used to extract $\mu$ principal component parameter features from $A_n$. It not only reduces the data dimension, but also retains the useful fault features [32]. And the detailed process is shown in Fig. 3.

III. BEARING FAULT DIAGNOSIS BASED ON STATE-SPACE PRINCIPAL COMPONENT TRACKING FILTER (SPCTF)

In this section, a novel method called state-space principal component tracking filtering (SPCTF) is proposed for fault diagnosis. Firstly, the switch Kalman filter (SKF) is utilized to establish dynamic filter model for time-series signals. And then, a feature tracking matrix is generated from the principal component features that is extracted from the optimal estimated state matrix of each time in the model. The optimal estimated state matrix is calculated with the optimal estimation at the previous time and the observation at the present time of the system. Thirdly, the principal component analysis is used to extract the effective fault feature from the redundant information generated in feature tracking matrix. Therefore, the proposed method can effectively eliminate the random interference to recover fault feature from polluted signal through the sequence of “Prediction – Measurement – Correction - Optimal estimation - Principal component extraction”. Finally, the envelope spectrum analysis is used to extract fault characteristic frequency to achieve high-precision fault diagnosis. The scheme of the proposed method based on SPCTF is briefly described in Fig. 4.
IV. SIMULATED SIGNAL VERIFICATION

A. SIMULATION SIGNALS

In order to verify the accuracy and reliability of the proposed method, there are two impulse response simulation signals is shown in (17) and (18). They are the raw outer race fault and outer race fault with noise respectively.

\[ x_o(t) = \sum_{i=1}^{N_o} \left[ e^{-\gamma_{2\pi f_{o1}(t-\tau)}^2} \sin \left( 2\pi f_{o1} (t - \frac{\tau}{f_{o1}}) \right) \sqrt{1 - \zeta^2} + e^{-\gamma_{2\pi f_{o2}(t-\tau)}^2} \sin \left( 2\pi f_{o2} (t - \frac{\tau}{f_{o2}}) \right) \sqrt{1 - \zeta^2} \right] \] (17)

\[ x_o(t) = \sum_{i=1}^{N_o} \left[ e^{-\gamma_{2\pi f_{o1}(t-\tau)}^2} \sin \left( 2\pi f_{o1} (t - \frac{\tau}{f_{o1}}) \right) \sqrt{1 - \zeta^2} + e^{-\gamma_{2\pi f_{o2}(t-\tau)}^2} \sin \left( 2\pi f_{o2} (t - \frac{\tau}{f_{o2}}) \right) \sqrt{1 - \zeta^2} \right] + w \] (18)

where the sampling frequency is \( f_s = 20000 \) Hz and the number of sampling points is \( N_o = 16384 \). \( x_o(t) \) is the simulation signal of a rolling bearing with an outer race fault, and the frequencies of its carrier centers are \( f_{o1} = 2000 \) Hz and \( f_{o2} = 5200 \) Hz. The damping ratio is \( \zeta = 0.05 \). \( w = 0.8 \times \text{random}(1, n) \) is the random white noise. The simulated signal according to (17) and (18) is shown in the Fig. 5.

B. RESULTS AND DISCUSSION

In this section, the comparative experiments, including envelope analysis and the reduced-order aggregate method based on balanced truncation approach (BTA), is implemented to prove the effectiveness of the proposed method. And the process of the proposed method is follow.

(i) 16384 data points are divided into 16380 groups, each group contains \( p = 5 \) data points (The number \( p \) is obtained from experience). (ii) the system state equation and prediction equation of the principal component tracking filter model are established according to (16). And then \( A = [a_1, a_2, a_3, a_4, a_5]^T \) is retained through 16380 generation with (9)-(14). (iii) the PCA is used to complete the final fault feature extraction and generate a fault feature matrix. (iv) the extracted fault features are analyzed by envelope spectrum to achieve high-precision fault diagnosis.

1) EVALUATION METRIC

There are two dimension parameters and three dimensionless parameters, including maximum value, peak-to-peak value, kurtosis, skewness and crest factor are selected to be treated as evaluation metric. The parameters are calculated according to the Table I. The \( x_{min} \) is the minimum value of the data.

| Symbol | Parameter | Formula |
|--------|-----------|---------|
| \( K \) | kurtosis | \( E[(X - \mu)^4] \) |
| \( S \) | skewness | \( \frac{(E[(X - \mu)^3])^2}{E[(X - \mu)^4]} \) |
| \( C \) | crest | \( \frac{E[(X - \mu)^2]}{\sqrt{\frac{1}{N} \sum_{i=1}^{N} x_i^2}} \) |
| \( \text{Max} \) | maximum peak to peak | \( x_{peak} \) |
| \( \text{Ptp} \) | peak to peak | \( x_{peak} \) |

2) EXPERIMENTAL RESULT

The comparison of dimension and dimensionless parameter characteristics of fault simulation signals processed by SPCTF is shown Table II. As a result, the evaluation metric representing impact components has changed significantly after pre-processing with SPCTF. Experiments show that the interference components in all signals are well suppressed, and the proposed method is effective for the bearing fault diagnosis.

| Signal | \( K \) | \( S \) | \( C \) | Max | Ptp |
|--------|--------|--------|--------|-----|-----|
| Raw (17) | 9.379 | 1.397 | 8.453 | 4.46 | 8.29 |
| SPCTF | 19.817 | 1.500 | 12.267 | 5.71 | 10.77 |
| Noisy (18) | 2.716 | 0.2415 | 5.623 | 4.75 | 9.35 |
| SPCTF | 5.448 | 0.3378 | 11.031 | 5.21 | 13.17 |

In order to further verify the superiority of the proposed method, the signal of state space is compared with the raw signal (out race fault simulation signals with noise). As shown in Fig. 6, the model tracking signals established by SPCTF can reduce the noise and retain the useful impact characteristics of the fault signal, which lays a good foundation for the next step to extract the effective fault feature.

FIGURE 5. The simulation fault signals. (a) Raw outer race fault; (b) Outer race fault with noise

FIGURE 6. The SPCTF tracking simulation signals comparison

The first principal component of PCA is retained to extract fault features. Fig. 7 shows the cumulative contribution rate of different principal components in PCA model in bearing fault simulation signal with noise. It can be concluded that the contribution rate of the first principal component has reached 89.3%, which contains most of the valid information.
in the model. Therefore, the first principal component is used as fault signal.

**FIGURE 7. Cumulative contribution rate**

![Graph](image)

**FIGURE 8. The fault bearing signals. (a) Original simulation signal; (b) SPCTF tracking signal; (c) First principal component characteristic signal.**

Furthermore, the original simulation signal, SPCTF tracking signal and the first principal component characteristic signal is shown in Fig. 8. The results show that the first principal component can accurately reflect the fault characteristics of the signal extracted by the principal component tracking filter model. The reason for the above experimental results is that SPCTF can effectively track the state of the system without pre information, which can effectively extract fault information from strong background noise based on anti-interference ability and real-time performance.

3) COMPARATIVE EXPERIMENT

The comparative experiment with envelop is performed for proving the effectiveness of the proposed method. And the envelop is used to analysis the raw signal. The experimental results are shown in Fig. 9. As shown in Fig. 9 (a), the eigenvalues of the principal component of the fault characteristic matrix have obvious periodic burst; the fault characteristic frequency (50 Hz) is vividly shown in Fig. 9(b). Then the outer race fault simulation signal with noise is used to carry out the fault diagnosis for the effectiveness of the proposed method facing with the noise. As shown in Fig. 9(c), the eigenvalues of principal components of signal fault characteristic matrix are affected with noise; and the envelope spectrum analysis results of principal components is shown in Fig. 9(d). There are obvious peaks at the fault frequency and its multiple frequency (50 Hz, 100 Hz, 150 Hz and 200 Hz) of the out race fault bearings, even though the noise causes the independent amplitude vibration of the signal. Fig. 9(e) is the envelop analysis of the unprocessed noise signals, which is difficult to identify fault characteristic frequency. The results show that the proposed method is effective for bearing fault diagnosis.

**FIGURE 9 The results decomposed by the proposed method. (a) The principal component eigenvalue of fault signals without noise; (b) The envelope analysis of principal component value; (c) The principal component eigenvalue of fault signals (noise); (d) The envelope analysis of principal component value. (e) The envelope analysis of noise signals.**

Moreover, the reduced-order method based on principal components analysis is utilized to extract the first principal component of optimal estimated state matrix, treated as
feature tracking matrix for generating characteristic parameters. For fairness, the proposed method is compared with the reduced-order aggregate model based on balanced truncation approach (BTA) [25] and result is shown in Fig. 10. As shown in Fig. 10, the noise signal is more obvious in BTA although the bearing fault features can be extracted with this method. The reason for this experimental result is the advantage of PCA: (i) PCA only needs to measure the amount of information by variance, which is not affected by factors other than the data set; (ii) The interactive factors between the components of the original data can be eliminated since the principal components are orthogonal.

FIGURE 10. Comparative experiment of reduced-order method

V. CASE STUDY
A. EXPERIMENT PLATFORM
In order to verify the effectiveness of SPCTF, raw signals of bearings in different states (normal, outer race fault, inner race fault, roller fault) were collected from experimental platform, as shown in Fig. 11 (a). The experimental device is composed of servo motor, load equipment, coupling and rotor system. There are three kinds of fault in the bearing (NSK 205) as shown in Fig. 11(b). The bearing failure is caused by manual cutting, the depth of damage is 0.25 mm and the width is 0.3 mm.

Vibration signals of bearings of different types of faults are measured by acceleration sensor (PCB ma352a60, PCB piezotronics Inc., New York, NY, USA). The signals sampling frequency is 100 kHz, the sampling time was approximately 3s. The fault characteristic frequencies are calculated according to [33]. The fault characteristic frequencies of inner race fault are shown in Table III. Moreover, there are three kinds of rotating speed in this research, including 500 rpm, 1000 rpm and 1500 rpm.

| TABLE III  |
| FAULT CHARACTERISTIC FREQUENCY (INNER 500 RPM) |
| Fault | Characteristic frequency |
| Outer race | 36.59Hz |
| Inner race | 55.07Hz |
| Roller | 39.67Hz |

FIGURE 11. Experimental platform. (a) The experimental device; (b) Fault bearings.

B. INTELLIGENT DIAGNOSIS WITH SPCTF
In this section, two dimension parameters and three dimensionless parameters, including maximum value, peak-to-peak value, kurtosis, skewness and crest factor are selected to be treated as evaluation metric (inner race fault signals is treated as an example). The comparative result between SPCTF and BTA are listed in Table IV. Although BTA is outstanding in the field of large-scale converters, the increase of the fault signals parameters characteristic index is more unforgettable in SPCTF.

Moreover, the envelope analysis of bearing inner race fault characteristic signal is shown in Fig. 12 and Table V. The calculated fault frequency of inner race fault signal is 55.1 Hz, 110.1Hz, 165.2 Hz, 220.3 Hz and 275.4 Hz. The fault characteristic frequencies obtained with SPCTF are 56.5 Hz, 111.4 Hz, 166.3 Hz, 221.3 Hz, and 276.2 Hz, which are in line with the calculated failure frequency of bearing inner race. As a result of the low signal-to-noise ratio of the actual bearing inner race fault signal, the envelope spectrum of the original signal incapable identify the fault characteristics. The effectiveness of the proposed method is proved.

TABLE IV
| DIMENSIONLESS PARAMETERS OF INNER RACE FAULT SIGNALS |
| K | S | C | Max | Ptp |
| RAW | 1.0558 | 0.7709 | 7.1191 | 11.988 | 29.392 |
| SPCTF | 4.9474 | 2.4499 | 9.8833 | 14.2811 | 33.2751 |
| BTA | 2.339 | 1.358 | 8.369 | 13.279 | 31.254 |

FIGURE 12. Inner race fault envelope spectrum
The outer race fault, roller fault and normal rolling bearings signals is analyzed, and the results are shown in Fig. 13 and Table VI. The experimental results show that the bearing fault types can be distinguished clearly by analyzing the envelope spectrum of fault characteristic principal component matrix extracted from SPCTF, which proves the effectiveness of the proposed method for actual bearing signal analysis.

C. COMPARATIVE EXPERIMENT

In order to verify the effectiveness and feasibility of the proposed method, Hilbert spectrum and high pass filtering methods were used for comparative experiments. The former (Hilbert spectrum) performs a Hilbert spectrum analysis on the raw signal filtered by Kalman and the proposed SPCTF. Moreover, the latter (high pass filtering) diagnoses and analyzes different types of fault signals (outer race, inner race, roller) under three speeds (500RPM, 1000RPM, 1500RPM).

1) HILBERT SPECTRUM EXPERIMENT

The comparative experiment based on Hilbert spectrum decomposes the original signal by EMD, and then calculates its Hilbert spectrum and Hilbert marginal spectrum. Hilbert spectrum emphasizes the local nature of the signal, which has a more intuitive physical meaning. The comparison experiment based on Hilbert spectrum is divided into three groups. The data used in the experiment are all under 500 RPM, each sample length is 16384, of which the first 8192 data are the outer race fault signals, and the last 8192 data are the inner race fault signals. In particular, Label 1 represents the raw signals; Label 2 represents the signals processed by traditional Kalman filtering; Label 3 represents the signal processing by SPCTF. It is intuitively identify the fault type through the Hilbert contour distribution of different kinds of fault signals. The experimental results are shown in Fig.14-16. As shown in Fig. 14, there are many false components in the spectrum of Hilbert signal due to the influence of system noise, which makes the distribution of spectrum contour map scattered. And the focus of real frequency is obviously poor, the outer race fault and inner ring fault cannot be effectively identified.
can be concluded that the main frequency band of Hilbert contour map of outer race fault is 0.5 Hz-0.8 Hz, while that of inner race fault is mainly 0.2 Hz-0.5 Hz, so as to clearly identify the fault type. Therefore, it is proved that the proposed SPCTF method can effectively removing the strong noise interference and lay a solid foundation for high-precision fault diagnosis.

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/
VI. CONCLUSIONS

A novel method based on state space principal component tracking filtering (SPCTF) is proposed for bearing fault diagnosis, which can remove noise interference and extract fault features effectively to realize high-precision bearing fault diagnosis. The proposed method is applied into simulation signals and actual vibration signal, and the experiment result demonstrates the effectiveness and feasibility. Moreover, the comparative experiment is performed with Hilbert spectrum method and high pass filter to verify the superiority of the SPCTF. The experimental results show that the fault types can be identified effectively by comparing the distribution of different fault signals in the Hilbert spectrum contour map. In addition, the proposed SPCTF bearing fault diagnosis method can effectively identify various bearing fault states under different speed conditions compared with the high pass filter, which verifies the generalization ability of SPCTF.

REFERENCES

[1] F. Piltan, J. M. Kim, “Bearing fault diagnosis using an extended variable structure feedback linearization observer,” Sensors, vol.18, no. 12, 4359, Dec. 2018.

[2] L. Bo, G. Xu, X. Liu, J. Lin, “Bearing fault diagnosis based on subband time-frequency texture tensor,” IEEE Access, vol.7, pp. 37611-37619, Feb. 2019.

[3] D. T. Hoang, H. J. Kang, “Rolling element bearing fault diagnosis using convolutional neural network and vibration image,” Cognitive Systems Research, vol. 53, pp. 42-50, Mar. 2018.

[4] V. Purushotham, S. Narayanan, S. A. Prasad, “Multi-fault diagnosis of rolling bearing elements using wavelet analysis and hidden Markov model based fault recognition,” Ndt & E International, vol. 38, no. 8, pp. 654-664, Apr. 2005.

[5] HD. Shao, HK. Jiang, XQ. Li, SP. Wu, “Intelligent fault diagnosis of rolling bearing using deep wavelet auto-encoder with extreme learning machine,” Knowledge-Based Systems, vol. 140, pp. 1-14, Oct. 2017

[6] Y. Lei, J. Lin, Z. He, M. J. Zuo, A review on empirical mode decomposition in fault diagnosis of rotating machinery, Mechanical systems and signal processing, vol. 35, pp. 108-126, Oct. 2012.

[7] X. Zhang, Y. Liang, J. Zhou, “A novel bearing fault diagnosis model integrated permutation entropy, ensemble empirical mode decomposition and optimized SVM,” Measurement, vol. 69, pp.164-179, Mar. 2015.

[8] M. Kedadouche, M. Thomas, A. J. M. S. Tahan, “A comparative study between Empirical Wavelet Transforms and Empirical Mode Decomposition Methods: Application to bearing defect diagnosis,” Mechanical Systems and Signal Processing, vol. 81, pp. 88-107, Mar. 2016.

[9] R. Abdelkader, A. Kaddour, Z. Derouiche, “Enhancement of rolling bearing fault diagnosis based on improvement of empirical mode decomposition denoising method,” The International Journal of Advanced Manufacturing Technology, vol. 97, no. 5, pp.3099-3117, Jul. 2018.

[10] X. Wang, Z. Yang, X. Yan, “Novel particle swarm optimization-based variational mode decomposition method for the fault diagnosis of complex rotating machinery,” IEEE/ASME Transactions on Mechatronics, vol.23, no. 1, pp. 68-79, Feb. 2018.

[11] C. Yi, Y., Lv, Z. Dang, “A fault diagnosis scheme for rolling bearing based on particle swarm optimization in variational mode decomposition,” Shock and Vibration, vol.2016, 9372691, May. 2016.
[12] S. Zhang, Y. Wang, S. He, Z. Jiang, “Bearing fault diagnosis based on variational mode decomposition and total variation denoising,” Measurement Science and Technology, vol. 27, no. 7, 075101, May. 2016.

[13] L. Wang, Z. Liu, Q. Miao, X. Zhang, “Time–frequency analysis based on ensemble local mean decomposition and fast kurtogram for rotating machinery fault diagnosis,” Mechanical Systems and Signal Processing, vol. 103, pp. 60-75, Oct. 2017.

[14] P. Shi, X. Ma, D. Han, A weak fault diagnosis method for rotating machinery based on compressed sensing and stochastic resonance. Journal of Vibration Engineering, vol. 21, no. 3, pp. 654-664, May. 2019.

[15] G. Li, J. Li, S. Wang, X. Chen, “Quantitative evaluation on the performance and feature enhancement of stochastic resonance for bearing fault diagnosis,” Mechanical Systems and Signal Processing, vol. 81, pp. 108-125, Feb. 2016.

[16] Z. Li, X. Liu, X. Wang, T. He, Y. Shan, “A multi-parameter constrained potential undamped stochastic resonance method and its application for weak fault diagnosis,” Journal of Sound and Vibration, vol. 459, 114862. Jul. 2019.

[17] H. Wang, P. Chen, “Fault diagnosis for a rolling bearing used in a reciprocating machine by adaptive filtering technique and fuzzy neural network,” WSEAS Transactions on Systems, vol. 7, no. 1, pp. 1-4, Jan. 2008.

[18] Z. Liao, L. Song, P. Chen, S. Zuo, “An automatic filtering method based on an improved genetic algorithm—with application to rolling bearing fault signal extraction,” IEEE Sensors Journal, vol. 17, no. 19, pp. 6340-6349, Oct. 2017.

[19] J. Long, H. Wang, D. Zha, P. Li, H. Xie, L. Mao, “Applications of fractional lower order S transform time frequency filtering algorithm to machine fault diagnosis,” PrOne, vol. 12, no. 4, e0175202, Apr. 2017.

[20] Z. Liu, L. Tang, L. Cao, “Feature Extraction Method for Rolling Bearing’s Week Fault Based on Kalman Filter and FSK,” Applied Mechanics and Materials, vol. 574, pp. 684–689, Jul. 2014.

[21] R. K. Singleton, E. G. Strangas, S. Aviyente, “Extended Kalman filtering for remaining-useful-life estimation of bearings,” IEEE Transactions on Industrial Electronics, vol. 62, no. 3, pp. 1781-1790, Mar. 2015.

[22] C. Anger, R. Schrader, U. Klingauf, “Unscented Kalman Filter with Gaussian Process Degradation Model for Bearing Fault Prognosis,” PHM Society European Conference, vol. 1, no. 1, pp.1-12, May. 2012.

[23] L. Cui, X. Wang, Y. Xu, H. Jiang, J. Zhou, “A novel switching unscented Kalman filter method for remaining use life prediction of rolling bearing,” Measurement, vol. 135, pp. 678-684, Dec. 2018.

[24] C. K. R. Lim, D. Mba, “Switching Kalman filter for failure prognostic,” Mechanical Systems and Signal Processing, vol. 52, pp. 426-435, Aug. 2014.

[25] R. Wang, Q. Sun, P. Tu, J. Xiao, Y. Gui, P. Wang, “Reduced-Order aggregate model for large-scale converters with inhomogeneous initial conditions in DC microgrids,” IEEE Transactions on Energy Conversion, 2021.

[26] X. Hu, H. Zhang, D. Ma, R. Wang, “A tnGAN-Based leak detection method for Pipeline network considering incomplete sensor data,” Access IEEE, vol.9, pp. 21735-21745, 2021.

[27] V. Manfredi, S. Mahadevan, J. Kurose, (2005, September). Access IEEE

[28] Z. Liu, L. Song, P. Chen, S. Zuo, “An automatic filtering method based on an improved genetic algorithm—with application to rolling bearing fault signal extraction,” IEEE Sensors Journal, vol. 17, no. 19, pp. 6340-6349, Oct. 2017.

[29] J. Long, H. Wang, D. Zha, P. Li, H. Xie, L. Mao, “Applications of fractional lower order S transform time frequency filtering algorithm to machine fault diagnosis,” PrOne, vol. 12, no. 4, e0175202, Apr. 2017.

[30] Z. Liu, L. Tang, L. Cao, “Feature Extraction Method for Rolling Bearing’s Week Fault Based on Kalman Filter and FSK,” Applied Mechanics and Materials, vol. 574, pp. 684–689, Jul. 2014.

[31] R. K. Singleton, E. G. Strangas, S. Aviyente, “Extended Kalman filtering for remaining-useful-life estimation of bearings,” IEEE Transactions on Industrial Electronics, vol. 62, no. 3, pp. 1781-1790, Mar. 2015.

[32] C. Anger, R. Schrader, U. Klingauf, “Unscented Kalman Filter with Gaussian Process Degradation Model for Bearing Fault Prognosis,” PHM Society European Conference, vol. 1, no. 1, pp.1-12, May. 2012.

[33] D. Appana, A. Prosvirin, J. Kim, “Reliable fault diagnosis of bearings with varying rotational speeds using envelope spectrum and convolution neural networks,” Soft Computing, vol. 22, no. 20, pp. 6719-6729, May. 2018.

[34] M. Hanadache, D. Lee, K. Veluvolu, “Rotor speed-based bearing fault diagnosis (RSBD) under variable speed and constant load,” IEEE transactions on industrial electronics, vol. 62, no. 10, pp. 6486-6495, Oct. 2015.

TANGSHAO DUAN received the M.S. degree in online analysis at Chongqing University of Science and Technology, Chongqing, China, in 2019. He is currently pursuing the Ph.D. degree in machinery fault diagnosis at Mie University, Tsu, Japan. His research interests include fault diagnosis of rotating equipment and intelligent algorithm.

Zhiqiang Liao received the Ph.D. degree from Mie University, Mie, Japan, in 2019. He is currently a temporary researcher of the Graduate School of Environmental Science and Technology, Mie University. His current research interests include equipment fault diagnosis technology, signal processing.

Taufi Li received the B.S., M.S., and Ph.D.degrees in mechanical engineering from Chongqing University, Chongqing, China, in 1996, 2000, and 2004, respectively. He is currently a Professor with the School of Electrical Engineering, Chongqing University of Science and Technology, Chongqing, China. His research interests include industrial process modeling and intelligent optimization.

Haihong Tang received the M.Sc. degree in Petroleum engineering, in 2018, from the Chongqing University of science and technology, Chongqing, China. She is currently working toward the Doctoral degree in the Graduate School of Environmental Science and Technology Mie University, Mie, Japan, in 2018. The topic of her doctoral research is intelligent fault diagnosis for machinery and signal processing.

Peng Chen received his Ph.D. degree from Kyushu University, Japan. He was an associate professor at Kyushu institute of technology. He is currently a professor at the Graduate School of Environmental Science and Technology, Mie University, Japan. His current research interests include machinery maintenance technology, plant equipment management technology, machinery condition monitoring and diagnosis technology, and intelligent robot system.