Spectral kurtosis based on evolutionary digital filter in the application of rolling element bearing fault diagnosis

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Abstract: Rolling element bearings are essential components in rotating machinery. It is important to detect the bearing fault as earlier as possible. It is known that spectral kurtosis (SK) is sensitive to impulse signal and has been widely used to detect bearing fault. Whereas, the incipient fault of bearing is weak and difficult to extract especially in a complex rotating system. Focusing on this issue, this study proposed a hybrid approach using evolutionary digital filter (EDF) and SK to detect rolling element bearing fault feature. Firstly, the signal to noise ratio of the raw signal was enhanced by EDF in a self-learning process. Then, the optimal band was detected using fast SK. Envelop analysis is later employed to extract the fault characteristic frequencies. The proposed approach was verified by numerical simulation and experimental analysis. Results show that the proposed SK-based EDF yields a good accuracy in bearing fault diagnosis.
Keywords: evolutionary digital filter; EDF; spectral kurtosis; fault diagnosis; bearing.


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1 Introduction

Rolling element bearings are the key components of rotating machinery, whose failure probability is higher than other components due to their poor working condition (Gu et al., 2020). Consequently, it is of great significance to ensure the reliability of rolling element bearings (Wang and Shao, 2020; Liu and Shao, 2017; Ding et al., 2019). Generally, the bearing fault can be detected by analysing modulation signals carried by high frequency signals. However, these modulation signals are easily submerged by the environmental noise. Therefore, many novel signal processing methods have been applied to the field of bearing fault diagnosis (Xiang et al., 2015).
Signal denoising plays an important role in bearing fault diagnosis. Signal with serious background noise increases the difficulty of fault feature extraction. Many existing methods eliminate noise by designing a sub-band filter (Zhou et al., 2009). However, in 1998, the empirical mode decomposition (EMD) was developed by Huang et al. (1998), and this method adaptively provides the amplitude-frequency modulated components called as intrinsic mode functions (IMFs) from signal. Therefore, many scholars tried to use EMD-based methods to obtain clean signals (Thirumalaisamy and Ansell, 2018; Niu et al., 2020). The EDF proposed by Abe and Kawamata (1997) is an adaptive filter which has been widely applied in machinery fault detection. An improved simplex-based adaptive evolutionary digital filter (EDF) has been presented to detect rolling element bearings fault (Xiao et al., 2014). Wang et al. proposed a new adaptive EDF based on alternately evolutionary rules to detect gear tooth spalling fault (Wang et al., 2019). By introducing the beehive pattern evolutionary rules into the original EDF, Zhou and Shao (2014) presented an improved beehive pattern evolutionary digital filter (BP-EDF) to overcome the defects of the original EDF.

Hilbert envelop analysis is widely used in fault diagnosis of bearings. And it is of great significance to select a frequency band which is related to the resonance of the bearing in envelope analysis (Bastami and Bashari, 2019). The real potential for finding resonance band of SK has been demonstrated in previous papers (Antoni, 2006). Therefore, many SK-based methods have been presented for fault detection. A method combining the EMD and SK is introduced to extract fault feature of rolling bearing (Jing et al., 2018). A novel method named empirical scanning spectrum kurtosis (ESSK) is proposed to maximally extract the periodic pulse components and accurately diagnose the faults of the rolling bearing (Xu et al., 2018). Wang et al. (2017) proposed a new method to solve the problem by using the meshing resonance and SK algorithms together.

Motived by these issues, a hybrid method combining EDF and SK is presented for accurate fault feature detection in the application of rolling element bearing. With a reference signal input, the desired features of the raw signal are firstly enhanced by EDF in a self-learning process. The optimal band is then designed using fast SK. Envelop analysis is later employed for the filtered signal to extract the fault frequencies. In these manners, the rest of the paper is organised as follows: Section 2 describes the proposed SK-based EDF method. Numerical simulation analysis is shown in Section 3. Experimental analysis with three comparisons is introduced in Section 4. Conclusions are drawn in Section 5.

2 Spectral kurtosis based on EDF

2.1 Adaptive algorithm of EDF

The EDF is a kind of adaptive filter which is based on the mechanics of natural selection with the strategies of cloning and mating. It consists of a series of linear/time-variant inner digital filters $W_i$ which correspond to individuals. Inner digital filter coefficients which correspond to the feature of individuals are controlled by the adaptive algorithm based on cloning and mating strategy. Figure 1 shows the block diagram of an EDF (Abe and Kawamata, 1997).
Figure 1  The block diagram of an EDF (see online version for colours)

Desired signal $d(k)$

Input $n(k)$

Filter $W_1$ $m_1(k)$ $e_1(k)$

Filter $W_2$ $m_2(k)$ $e_2(k)$

Filter $W_n$ $m_n(k)$ $e_n(k)$

Updating the coefficients of inner filters

Evaluation of inner filters

$\sum m_1(k) e_1(k)$

$\sum m_2(k) e_2(k)$

$\sum m_n(k) e_n(k)$

$\sum_{m=1}^{n} m_i(k) e_i(k)$

Output $y(k)$

Select the output $y_3(k)$

Figure 2  Schematic plot of EDF adaptive rules (see online version for colours)

Fitness value

High

Family establishment

Selection

Sort

Grouping

$i++$

Clone group ($N/2$)

Mating

Parents

Offspring

$i$th generation

$(i+1)$th generation

Fitness value

Low

$i$th generation

$\sum_{m=1}^{n} m_i(k) e_i(k)$

Figure 2 illustrates the adaptive rules of EDF from $i$th generation to $(i+1)$th generation. And the detailed steps of the rules are shown as follow (Wang et al., 2019):
Step 1  Grouping. All the individuals will be equally divided into two groups according to their fitness values.

\[
W = \begin{bmatrix}
    W_H &=& [w_1', w_2', ..., w_{N/2}']^T \\
    W_L &=& [w_{(N/2+1)}', w_{(N/2+2)}', ..., w_N']^T
\end{bmatrix}
\tag{1}
\]

\[
f(w_i' | w_i' \in W_H) \geq f(w_j' | w_j' \in W_L)
\tag{2}
\]

where \( w_i' \) is the \( i \)-th individual in the \( r \)-th generation, \( f(\bullet) \) is the fitness function, \( N \) is the population size.

Step 2  Family establishment. Several offspring individuals which are similar to their parents are generated by cloning. The strategy of cloning is an asexual reproduction method which can ensure to find the best individuals near the parent individuals. Simultaneously mating strategy is a sexual reproduction method. Two parents from mate group are randomly selected to get the excellent offspring individuals.

\[
\begin{align*}
\widetilde{W}_1 &= \begin{bmatrix}
    w_1' & w_2' & \cdots & w_{N/2}^{r+1} \\
    w_2' & w_3' & \cdots & w_{N/2}^{r+1} \\
    \vdots & \vdots & \ddots & \vdots \\
    w_{N/2}' & w_{N/2}^{r+1} & \cdots & w_{N/2}^{r+1}
\end{bmatrix} \\
\widetilde{W}_2 &= \begin{bmatrix}
    w_{N/2+1}' & w_{N/2+2}' & \cdots & w_{N/2+1}^{r+1} \\
    w_{N/2+2}' & w_{N/2+3}' & \cdots & w_{N/2+1}^{r+1} \\
    \vdots & \vdots & \ddots & \vdots \\
    w_{N/2+1}' & w_{N/2}^{r+1} & \cdots & w_{N/2}^{r+1}
\end{bmatrix}
\end{align*}
\tag{3}
\tag{4}
\]

where \( \widetilde{W}_1 \) and \( \widetilde{W}_2 \) are the new families that generated by cloning and mating evolutionary strategies, respectively. And \( N_c \) and \( N_m \) respectively represent the offspring numbers that produced by cloning and mating evolutionary strategies, where each row represents one family in those family matrixes.

Step 3  Selection. In clone group, the individual with maximum fitness value is selected in each family. In mate group, the parent with higher fitness value and the offspring in each family will survive while the other parent die out.

\[
W_i' = \widetilde{W}_i S_1 = \begin{bmatrix}
    w_1' & w_2' & \cdots & w_{N/2}\Nc' \\
    w_2' & w_3' & \cdots & w_{N/2}\Nc' \\
    \vdots & \vdots & \ddots & \vdots \\
    w_{N/2}' & w_{N/2+1}' & \cdots & w_{N/2+1}\Nc'
\end{bmatrix} \begin{bmatrix}
    1 & 0 & \cdots & 0 \\
    0 & 1 & \cdots & 0 \\
    \vdots & \vdots & \ddots & \vdots \\
    1 & 0 & \cdots & 0
\end{bmatrix} = \begin{bmatrix}
    w_1' \\
    w_2' \\
    \vdots \\
    w_{N/2}'
\end{bmatrix}
\tag{5}
\]
where $W'_1$ and $W'_2$ respectively denote the selected families of the clone group and mate group, and $S_1$ and $S_2$ are the corresponding selection matrix with a binary value.

Step 4 Sort. All the selected individuals are sorted according to the fitness value in a descending order.

The EDF can search a global optimum effect in the multiple-peak surface and has a smaller adaptation noise level than the other algorithms. Meanwhile, the EDF has a higher convergence rate and smaller adaptation noise than some other adaptive digital filters on a multiple-peak surface.

2.2 Spectral kurtosis

Kurtosis is a statistical index in time domain, and it is very sensitive to fault impact components. In order to extract the transient information and find the hidden non-stationarity of a signal, Dwyer first introduces kurtosis into the frequency domain and proposed the concept of frequency kurtosis (Dwyer, 1983). Antoni (2006) gave the formal definition of spectral kurtosis (SK) based on the World-Cramer decomposition. And in order to connect the theoretical concept with the practical application, he developed the fast algorithm of SK.

The Wold-Cramer decomposition spectrum of signal $X(t)$ is defined as

$$Y(t) = \int_{-\infty}^{\infty} e^{j2\pi ft}H(t, f; \omega)dX(f)$$

where $Y(t, f; \omega)$ is a complex envelope whose shape depends on the outcome $\omega$. The fourth-order spectral cumulant of a conditionally non-stationary process is defined as:

$$C_{4f}(f) = S_{4f} - 2S^2_{2f}(f), \quad f \neq 0$$

where $S_{2n}(f)$ is the $2n$ order instantaneous moment and it is defined as:

$$S_{2n}(f) = E\left\{H(t, f)dX(f)^{2n}\right\}/df$$

Thus, this so-called SK can be obtained as:

$$K_{f}(f) = \frac{C_{4f}(f)}{S^2_{2f}(f)} - S_{4f}(f)/S^2_{2f}(f) - 2, \quad f \neq 0$$

2.3 The proposed SK-based EDF method

As we known, the fault feature is easily disturbed by the interference of the external noise where the parameters of the band-pass filter are hard to be selected for an accurate
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In this manner, this study combines the EDF with SK analysis, which aims to reduce the noise influence in a self-learning process for filter parameters. This specific process is illustrated in Figure 3. First, the raw fault signal combined with the reference signal are put into the EDF for filter parameters learning, thus the desired features, which indicate the crucial fault information, can automatically enhanced. Thus, an optimal band-pass filter can be further reached via fast SK, and it will lead a clear spectral distribution for an accurate diagnosis.

Figure 3  Flow chart of the proposed SK-based EDF method (see online version for colours)

3 Simulation analysis

In this section, a simulation signal with a noise of –15 dB is used to verify the effectiveness of the proposed method. The simulated bearing fault signal can be expressed as:

\[ s(t) = e^{-bt} \left[ \sin 2\pi f_{c1} t + 1.2 \sin 2\pi f_{c2} t \right] + n(t) \]  

(11)

\[ \alpha = \text{mod}(t, 1/f_r) \]  

(12)

where \( b \) is the exponential frequency with a value of 300, \( f_{c1}, f_{c2} \) (\( f_{c1} = 1,000 \) Hz and \( f_{c2} = 3,000 \) Hz) and \( f_r \) (\( f_r = 50 \) Hz) are respectively those two kinds of carrier frequencies and modulation frequency. And \( n(t) \) is a white noise with a level of –15 dB. A simulated impulse signal consisted of five impulses in a time interval of 0.02 s as shown in Figure 4(a) while the waveform of noise \( n(t) \) is displayed in Figure 4(b).
**Figure 4** The simulated signal, (a) the raw impulses (b) the noise component (see online version for colours)

Figures 5(a) and 5(b) respectively represent the fault signal covered with noise and the reference signal, where the reference signal is related to the noise signal $n(t)$ but has different amplitude and phase information. From the spectrums as listed in Figures 5(c)~5(d), it can be obviously found that the noise significantly weakens the periodic characteristic of the raw signal and the fault feature cannot be detect from the frequency spectrum.

**Figure 5** The waveforms of the simulated signal, (a) the fault signal (b) the reference signal, (c) the frequency spectrum of (a) and (d) the envelop spectrum of (a) (see online version for colours)

First, the EDF is applied to noisy signals, then the denoised signal is analysed with SK method to get the kurtogram shown in Figure 6(a), where we can see that the centre frequency corresponding to the maximum value of kurtosis is 3,200 Hz, and the corresponding filtering band is [2,560, 3,840] Hz. Spectrum and envelop spectrum of the filtered signal is shown in Figure 6(b) and Figure 6(c), respectively. In Figure 6(c), we can distinguish the fault characteristic frequency $f_r = 50$ Hz, $2f_r = 100$ Hz and $3f_r = 150$ Hz. The simulation result shows that the proposed method is effective for fault detection of the rolling element bearing.
Figure 6  The EDF-based results of the simulated signal, (a) convergence curve and (b) envelope spectrum (see online version for colours)

Figure 7  The SK-based results of the simulated signal, (a) kurtogram of the raw signal, (b) spectrum and (c) envelope spectrum of the optimal band (see online version for colours)

Figure 8  The results of the proposed SK-based EDF method, (a) kurtogram of the denoised signal, (b) spectrum of the optimal band and (c) envelope spectrum of the optimal band (see online version for colours)
4 Experimental verification

In order to further verify the effectiveness of the proposed method, the experimental analysis is carried out by experimental system shown in Figure 9, which consists mainly of motor, two-stage parallel shaft gearbox, magnetic powder brake, acceleration sensors and data acquisition system. A detect is introduced on the inner race of the tested bearing.

Figure 9 Experimental system, (a) location of acceleration sensors and (b) test rig (see online version for colours)

The parameters of the gearbox transmission system are listed in Table 1. The fault characteristic frequency of the bearing inner race can be calculated as:

\[ f_{BPFI} = \frac{1}{2} f_r z \left(1 + \frac{d}{D} \cos \alpha \right) \]

where \( f_r \) is rotational frequency, \( z \) is the number of elements, \( \alpha \) is the contact angle, \( d \) and \( D \) are respectively the ball and pitch diameters. According to the parameters of the tested bearing, the fault characteristic frequency \( f_{BPFI} \) is equal to 147.8 Hz.

Table 1 Parameters of the transmission system

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pitch diameter of the fault bearing D (mm)</td>
<td>65</td>
</tr>
<tr>
<td>Ball diameter d (mm)</td>
<td>15.081</td>
</tr>
<tr>
<td>Number of elements z</td>
<td>8</td>
</tr>
<tr>
<td>Contact angle ( \alpha )(°)</td>
<td>0</td>
</tr>
<tr>
<td>Sampling frequency ( f_s ) (Hz)</td>
<td>10,240</td>
</tr>
<tr>
<td>Sampling data length L</td>
<td>20,480</td>
</tr>
<tr>
<td>Sampling time t (s)</td>
<td>2</td>
</tr>
<tr>
<td>Rotational frequency ( f_r ) (Hz)</td>
<td>30</td>
</tr>
</tbody>
</table>

The original vibration signals measured from the gearbox house and the motor are respectively shown in Figure 8. As illustrated in Figure 10, it can be seen that the given fault is attached in the gearbox which is far away from the motor. In this manner, it can be assumed that the desired information related to the fault gear mainly distributed in the signal provided by sensor B, and the remained signal provided by sensor A can reflect the background signal, which has less correction with the fault information. Therefore, the signal from motor is treated as the reference signal, and the waveforms of these two
signals are shown in Figures 10(a) and 10(b), respectively. The corresponding spectrum and envelop spectrum of the fault signal are also drawn in Figures 10(c) and 10(d). It can be seen that several impulses can be observed from those two vibration signal collected from the experimental system. However, it is hard to identify whether it is the desired fault information while the fault components are masked by noise and not evident enough. Especially, as shown in Figures 10(c)–10(d), the fault frequency $f_{BPFI}$ of the signal provided by sensor B, with a detect on bearing inner race, has been heavily covered by the noise inference. In this manner, it is crucial to extract the principle fault information for an accurate fault diagnosis.

Figure 10 The waveforms of the acquired signals, (a) the fault signal from the gearbox, (b) the reference signal from motor, (c) spectrum of (a), (d) envelop spectrum of (a) (see online version for colours)

For an accurate fault detection effect, the proposed SK-based EDF method is first employed here, and the results are shown in Figure 11. As shown in Figure 11(a), the kurtogram indicates that the centre frequency corresponded to the maximum kurtosis value is 3520 Hz, and the corresponding filtering band is [3,200, 3,840] Hz, which is very consistent with the distribution of the bearing structure characteristic. And its frequency spectrum of the filtered signal is also clearly shown in Figure 11(b). According to the envelop spectrum in Figure 12(c), we can find that the fault characteristic frequency $f_{BPFI}$ and its harmonics modulated by the rotational frequency $f_r = 30 \text{ Hz}$ can be well distinguished. This indicates that this proposed SK-based EDF method can not only precisely give the optimal frequency band but also abundantly provide a sound diagnosis spectrum.
Figure 11  The results of the proposed SK-based EDF method, (a) kurtogram of the denoised signal, (b) spectrum and (c) envelope spectrum of the filtered signal (see online version for colours)

For a better illustration, there other diagnosis methods, including the mentioned EDF, SK and an improved SK-based EMD method, are also verified here. First, for the same case that the signal in Figure 10(a) with a reference signal Figure 10(b) are used to test the EDF method. Following equations (5)–(6), the convergence curve of EDF is shown in Figure 12(a), and the fault characteristic frequency $f_{BPFI}$ with its $2f_{BPFI}$ show a slightly clearer distribution. However, there are still lots of interfering components, such as the gear frequency, which affects the accuracy of fault diagnosis. Secondly, the SK-based method is also applied to analyse the original signal separately. The kurtogram is shown in Figure 13(a), where we can see that the centre frequency with the maximum kurtosis value is 853 Hz, and the corresponding filtering band is $[0, 1,706]$ Hz. The spectrum and envelop spectrum of the filtered signal are shown in Figure 13(b) and Figure 13(c), respectively. There is a fact that, because the frequency band is not correctly selected, the fault information could not be well identified for the fault frequency $f_{BPFI}$ covered by noise.

Figure 12  The EDF-based results of the fault signal, (a) convergence curve, (b) envelop spectrum (see online version for colours)
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**Figure 13** The SK-based results of the fault signal, (a) kurtogram of the raw signal, (b) spectrum and (c) envelope spectrum of the filtered signal (see online version for colours)

![Image](image1)

**Figure 14** The results of EMD-SK method, (a) kurtogram of the denoised signal, (b) spectrum and (c) envelope spectrum of the filtered signal (see online version for colours)

![Image](image2)

**Source:** Jing et al. (2018)

Furthermore, The EMD-SK method in Jing et al. (2018) is also used here to detect the fault components. The kurtogram is shown in Figure 14(a), where we can see that the centre frequency corresponded to the maximum kurtosis value is 2,986 Hz, and the corresponding filtering band is [2,560, 3,410] Hz, where the spectrum and envelope spectrum of this filtered signal are shown in Figures 14(b) and 14(c), respectively. In that same situation, due to the incorrect selection for the desired frequency band, no fault components can be detected at all, which means that this method will lead a wrong fault diagnosis effect.

Mean-peak ratio (MPR) (Widodo et al., 2009) is utilised as a metric to assess the performance of different methods. It can be calculated as:
where $N$ is the harmonic frequency order of fault characteristic frequency, and $N$ is set as 3 in this paper. $F_i$ represents the fault frequency amplitude of $i^{th}$ order in the envelop spectrum. $A_i$ is the mean value of amplitude from $a^{th}$ line to $b^{th}$ line. $S_j$ denotes the amplitude of the $j^{th}$ line in the envelop spectrum.

Table 2 compares the MPR values of the proposed SK-based EDF method and other methods. It can be seen that the proposed method has the larger MPR value for both inner race fault and outer race fault. According to (14) and (15), the larger the MPR number, the better the demodulation effect. It should be noted that VMD-SK method (Gu et al., 2020) and PPCA-SK (Xiang et al., 2015) method are basically similar to the EMD-SK method.

Table 2  Comparison of MPR value of different methods (dB)

<table>
<thead>
<tr>
<th>Fault type</th>
<th>EDF-SK</th>
<th>EDF</th>
<th>SK</th>
<th>EMD-SK</th>
<th>VMD-SK</th>
<th>PPCA-SK</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inner race fault</td>
<td>29.80</td>
<td>23.88</td>
<td>8.92</td>
<td>10.41</td>
<td>8.80</td>
<td>7.35</td>
</tr>
<tr>
<td>Outer race fault</td>
<td>32.84</td>
<td>25.47</td>
<td>9.58</td>
<td>9.63</td>
<td>14.4</td>
<td>14.03</td>
</tr>
</tbody>
</table>

5 Conclusions

In this study, to overcome the problem of the crucial fault feature identification in a self-learning way, a SK-based EDF method is proposed to achieve a high accuracy of bearing fault detection. Different from the conventional filtering methods, the desired fault feature will be automatically enhanced with a reference signal. Specially, the optimal frequency band with a clear feature distribution can be further well searched for accurate fault feature detection. The numerical simulation and experimental results validate the effectiveness of the proposed method in extracting weak characteristics and diagnosing faults of rolling element bearings. Compared with other methods, the proposed method has good performance in noise reduction and detection of transient impact component of the rolling element bearings. It can be also foreseen that this automatic learning process with accurate feature identification is of great significance in practical intelligent diagnosis application.

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