Fault detection for rolling element bearing using an enhanced morphological-hat product filtering method

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Abstract. A novel morphological filter (MF), named enhanced morphological-hat product filtering (EMHPF) is proposed for bearing fault detection. Within this method, a new morphological-hat product operation (MHPO) is firstly proposed based on two morphological-hat operators that are previously reported. Subsequently, an efficient evaluation index called fault feature ratio (FFR) is applied to select adaptively the length of structuring element (SE) for improving the precision of bearing fault diagnosis. The simulation and experimental results on rolling bearing fault illustrate that the proposed EMHPF method is capable of enhancing fault detection of rolling bearing, and its feature extraction capability is superior to that of some existing morphological filter methods.

1. Introduction

As is well known, bearing vibration feature caused by partial failure are usually characterized by periodic impulses. However, these periodic impulse components connected with bearing fault are always submerged and distorted by various interferences, such as discrete harmonic components and Gaussian background noise [1]. Therefore, it is a difficult problem about how to obtain useful fault characteristics from bearing vibration signal. At present, various feature extraction methods have been developed for extracting the inherent fault characteristics of bearing vibration signal, such as wavelet analysis and Empirical mode decomposition. However, these methods have some shortcomings. Therefore, research on a novel fault diagnosis method is the focus of this article.

Morphological filtering is a nonlinear signal processing method and has been widely used in the field of mechanical fault detection [2]. Compared with the conventional filtering algorithm (e.g. Finite impulse response (FIR) and Butterworth filter), morphological filtering is more simple and easier to be realized with high efficiency. The current morphological filtering is mainly divided into two types, that is, noise reduction-type and feature extraction-type [3]. The familiar noise reduction-type morphological filtering has dilation, erosion, opening and closing, whereas the common feature extraction-type morphological filtering includes white top-hat (WTH) and black top-hat (BTH), average-hat (AVGH) [4] and combination morphological filter-hat transform (CMFH) [5] etc. At present, AVGH and CMFH have been proved to be effective in extracting periodic impulse components related to bearing fault, and the two operators has good anti-noise and robust performance. Hence, considering the advantages of AVGH and CMFH, the morphological-hat product operation (MHPO) is proposed in this paper. Meanwhile, a potential quantitative measure index named fault feature ratio (FFR) is adopted to promote fault detection ability of MHPO.
The outline of this paper is as follows. Section 2 reviews the reported morphological filtering. Section 3 presents the general process of the proposed approach for bearing fault detection. In Section 4, a bearing fault simulation signal is designed to validate the effectiveness of the proposed method. Section 5 applies the proposed method to analyze the experimental bearing fault data. Conclusions are drawn in Section 6.

2. The reported morphological filtering

Set \( f(n) \) as a discrete one-dimensional signal over a domain \( F = (0,1,\cdots,N-1) \), set \( g(m) \) as the structuring element (SE) over a domain \( G = (0,1,\cdots,M-1) \), where \( N \geq M \) and \( m \in 0,1,\cdots,M-1 \). The dilation and erosion operations of signal \( f(n) \) are respectively defined as:

\[
(f \oplus g)(n) = \max[f(n-m) + g(m)]
\]

\[
(f \ominus g)(n) = \min[f(n+m) - g(m)]
\]

Morphology gradient (MG) is defined as the difference of dilation and erosion operator

\[
MG(f(n)) = (f \oplus g)(n) - (f \ominus g)(n)
\]

The opening and closing operations is further defined as:

\[
(f \circ g)(n) = (f \ominus g \oplus g)(n)
\]

\[
(f \bullet g)(n) = (f \oplus g \ominus g)(n)
\]

Where denotes the opening operator and \( \bullet \) denotes the closing operator. Average operator between the closing and opening operator (AVG) is expressed as:

\[
AVG(f(n)) = \frac{(f \bullet g)(n) + (f \circ g)(n)}{2}
\]

Difference operator of the closing and opening operator (DIF) is defined as [6]

\[
DIF_{C\&O}(f(n)) = (f \bullet g)(n) - (f \circ g)(n)
\]

\[
= [f(n) - (f \circ g)(n)] + [(f \bullet g)(n) - f(n)]
\]

\[
= WTH(f(n)) + BTH(f(n))
\]
Where $WTH(f(n))$ is WTH, which is used to obtain the positive impulses, $BTH(f(n))$ is BTH, which is used to obtain the negative impulses. Integrating AVG and WTH, AVGH operator is formulated as:

$$AVGH(f(n)) = 2f(n) - ((f \cdot g)(n) + (f \circ g)(n))$$  \hspace{1cm} (8)

The opening-closing (OC) and closing-opening (CO) operator are respectively defined as

$$FOC(f(n)) = (f \circ g \cdot g)(n)$$  \hspace{1cm} (9)

$$FCO(f(n)) = (f \cdot g \circ g)(n)$$  \hspace{1cm} (10)

Combination morphological filter (CMF) and difference operator between the FCO and FOC are respectively defined as

$$CMF(f(n)) = \frac{FCO(f(n)) + FOC(f(n))}{2}$$  \hspace{1cm} (11)

$$DIF_{CO\&OC}(f(n)) = FCO(f(n)) - FOC(f(n))$$  \hspace{1cm} (12)

Integrating CMF and WTH, CMFH operator is expressed as follows [7]

$$CMFH(f(n)) = f(n) - \frac{FCO(f(n)) + FOC(f(n))}{2}$$  \hspace{1cm} (13)

Morphology gradient product operation (MGPO) is defined as arithmetic product between the FOC and FCO [8]

$$MGPO(f(n)) = DIF_{CO\&OC}(f(n)) \cdot DIF_{CO\&OC}(f(n))$$  \hspace{1cm} (14)

3. The proposed EMHPF fault detection scheme

3.1. Morphological-hat product operation

Integrating AVGH with CMFH, a new operator termed as MHPO can be formulated as

$$MHPO(f(n)) = AVGH(f(n)) \cdot CMFH(f(n))$$  \hspace{1cm} (15)

3.2. Fault feature ratio

For a given signal $x(t)$, its FFR can be defined as
\[ R_f = \frac{Y^2(f) + Y^2(2f) + Y^2(3f)}{\sum_{j=1}^{n} Y^2(f_j)} \]  

Where \( f \) is the fault characteristic frequency, \( Y(kf) \) is amplitude at the \( k \)th harmonic of fault characteristic frequencies, \( Y(f_j), j = 1, 2, \ldots, n \) is envelope spectrum amplitude of the signal \( x(t) \).

3.3. The proposed EMHPF fault detection scheme

Based on MHPO and FFR, the EMHPF-based fault diagnosis scheme is presented in this paper. Figure 1 shows flowchart of the proposed EMHPF fault detection scheme. Details of the proposed method can be described as follows:

1. Using acceleration transducer to collect the bearing fault signal.
2. Initializing the range of SE length. Due to flat SE has the advantages of simple structure and fast operation speed compared with a semicircle and triangle SE, so this paper selects the flat SE. In this step, the selected flat SE height is zeros, whereas the flat SE length is set as 3 to \( L_{\text{max}} \), where \( L_{\text{max}} \) is the maximal length of SE and meets \( L_{\text{max}} = \lceil f_s / f_g \rceil \), where \( f_s \) represents sampling frequency, \( f_g \) stands for defect frequency and \( \lceil \cdot \rceil \) means the round-off number.
3. Conducting MHPO at each SE length, and calculating FFR of the filtering results.
4. Finding the largest FFR and obtaining the optimal SE length corresponding to the largest FFR.
5. Conducting EMHPF with the optimal SE length, and calculating FFT spectrum of the EMHPF results to identify bearing fault types.

\[ x(t) = \exp(-100t_0)(\cos(2\pi f_1 t) + \sin(2\pi f_2 t) + \sin(2\pi f_3 t) + n(t)) \]  

where \( t_0 = \text{mod}(k/f_s, f_g), k = 0, 1, \ldots, 2047 \), sampling frequency and signal length respectively are 2048 Hz and 2048 points, natural frequency of bearing system is \( f_1 = 200 \) Hz, vibration frequencies caused by other components respectively are \( f_2 = 30 \) Hz and \( f_3 = 40 \) Hz, fault characteristic frequency of bearing \( f_g = 16 \) Hz, \( n(t) \) is the Gaussian noise with SNR of 3 dB. Figure 2 describes the simulation waveform and its corresponding FFT spectrum and envelope spectrum. From Figure 2 we cannot
observe the defect frequency of 16 Hz. This indicates that conventional spectral analysis is ineffective in extracting bearing fault feature in this case.

The proposed method is used to analyze the bearing fault simulation signal and the analyzed results are shown in Figure 3. Figure 3(a) is the relation curve between SE length and FFR value, where the largest FFR value is corresponding to SE length L=8, so optimal SE length is selected as L=8. Figure 3(b) shows the filtering results achieved using MHPO with optimal SE length L=8. Figure 3(c) is FFT spectrum of the optimal filtering results. It can be seen clearly from Figure 3(c) that fault feature frequencies (16 Hz and its harmonics) are clear, which implies that the proposed EMHPF is effective in detecting the fault feature frequencies from bearing fault simulation signal.

Figure 3. Diagnostic results of the proposed method for bearing fault simulation signal: (a) FFR curve, (b) the filtering signal obtained by optimal MHPO, and (c) FFT spectrum of (b).

5. Experimental validation

5.1. Experimental system description and data collection

Bearing fault experiment is performed to validate the presented method. Experimental data was collected from the Machinery Fault Simulator (ABLT-1A). Experimental device is shown in Figure 4(a), which is mainly composed of drive system, loading system, lubrication system, test block and bearing block. The inner race fault is implanted on the surface of bearing through using electric spark machining. The faulty bearing with an inner race is shown in Figure 4(b). The faulty bearing was located at right side of the shaft and a normal bearing on the left. Table 1 lists the size parameters of rolling bearing. The motor rotation speed during experiment was 1050 rpm. A PCB accelerometer was installed on the vertical direction of bearing housing of the analyzed bearing to collect the fault data.
The sampling frequency and sampling number respectively are 10240 Hz and 8192 points. According to the theoretical formula, bearing inner race fault feature frequency is calculated as \( f_i = 94.76 \) Hz.

The bearing inner race fault signal and its FFT spectrum and envelope spectrum are presented in Figure 5. It is hard to observe any defect feature from FFT spectrum and envelope spectrum of Figure 5(c) because of the heavy background noise.

![Figure 4](image)

**Figure 4.** (a) Bearing fault simulation device and (b) bearing with an inner race fault.

| Roller diameter | Pitch diameter | Roller number | Contact angle |
|-----------------|----------------|---------------|---------------|
| 7.94 mm         | 39.04 mm       | 9             | 0°            |

**Table 1.** Parameters of bearing.

![Figure 5](image)

**Figure 5.** (a) Bearing inner race fault signal, (b) FFT spectrum of (a), and (c) envelope spectrum of (a).

5.2. The proposed method analysis

Bearing inner race fault signal is analyzed by the presented method. Figure 6(a) shows the relation curve between SE length and FFR value. From Figure 6(a), we can know that the optimal SE length is also set as \( L = 8 \). Figure 6(b) displays the filtering results obtained by MHPO containing the optimal SE length \( L = 8 \). Envelop spectrum of the filtering results is shown in Figure 6(c). It is obvious from Figure 6(c) that the defect frequencies \( f_i \) and its harmonics (i.e. \( 2f_i \) and \( 3f_i \)) can be found effectively in envelop spectrum of the filtering signal, which means that the presented approach can detect the inner race fault resided in rolling bearing.
6. Conclusion

A new fault diagnosis scheme based on EMHPF is proposed for enhancing fault detection of rolling bearing. Firstly, based on AVGH and CMFH, MHPO is presented to process the collected bearing vibration signal. Then, FFR is employed to select automatically the optimal SE length of MHPO for the purpose of enhancing bearing fault detection. Finally, FFT spectrum of the filtering signal obtained by EMHPF is calculated to complete the fault diagnosis of rolling bearing. The proposed method is demonstrated by using simulation signal and experimental examples. The experimental results indicate that the proposed EMHPF is not only simple but also effective for bearing fault diagnosis.

Acknowledgments

This work was financially supported by the National Natural Science Foundation of China (Grant No. 51675098) and Postgraduate Research & Practice Innovation Program of Jiangsu Province, China (Project No. KYCX17_0059).

References

[1] Z. Feng, M. Liang, F. Chu, Recent advances in time–frequency analysis methods for machinery fault diagnosis: a review with application examples, Mech. Syst. Signal Process. 38 (2013) 165-205.
[2] N.G. Nikolaou, I.A. Antoniadis, Application of morphological operators as envelope extractors for impulsive-type period signals, Mech. Syst. Sig. Process. 17 (6) (2003) 1147-1162.
[3] Y. Li, X. Liang, M.J. Zuo, A new strategy of using a time-varying structure element for mathematical morphological filtering, Measurement 106 (2017) 53-65.
[4] F. Deng, S. Yang, G. Tang, et al, Self adaptive multi-scale morphology AVG-Hat filter and its application to fault feature extraction for wheel bearing, Meas. Sci. Technol. 28 (2017) 045011.
[5] A. Hu, L. Xiang, Selection principle of mathematical morphological operators in vibration signal processing, J. Vib. Control 43 (2) (2014) 420-425.
[6] A.S. Raj, N. Murali, Early classification of bearing faults using morphological operators and fuzzy inference, IEEE Trans. Ind. Electron. 60 (2) (2013) 567-574.
[7] X. Yan, M.Jia, W. Zhang, L. Zhu, Fault diagnosis of rolling element bearing using a new optimal scale morphology analysis method, ISA Trans. 73 (2018) 165-180.
[8] Y. Li, M.J. Zuo, Y. Chen, et al. An enhanced morphology gradient product filter for bearing fault detection, Mech. Syst. Signal Process. 109 (2018) 166-184.