Local Mean Decomposition and Weighted Kurtosis Index for Bearing Defect Detection

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Abstract: Vibration signal analysis is an effective technique for detecting bearing defects, and it proposes an approach that involves signal processing methods to extract information about the defects. The initial step in the proposed approach involves dividing the signal into several components (PF) using the LMD algorithm. Subsequently, the weighted kurtosis index (WKI) values are computed, and the summation of components having WKI values higher than the average of WKI leads to the formation of a new signal containing multiple pulses that are very similar to the original signal. Then we can observe peaks at the frequencies of the bearing defects in the envelope spectrum of the new signal. Applying the proposed approach to the vibration signal available in the XJTU database shows a peak at the fault frequency of the outer ring.

Keywords: Bearing, Weighted kurtosis, Fault detection, Frequency

1. INTRODUCTION

Rotating machinery relies heavily on bearings, which are often exposed to significant forces during operation, an essential measure to avoid machine down is to monitor the bearing condition since a failed bearing can put the machine at risk [1]. To diagnose bearing defects accurately, the most effective method involves analyzing vibration signals collected by a measuring system that comprises a sensor mounted on the bearing housing [1].

When a bearing develops a fault during operation, it generates a vibratory shock that modulates the amplitude of the vibration and creates pulses [2]. There are several methods of processing and extracting fault characteristics that can be classified into three categories: time domain, frequency domain, time-frequency domain [3]. The methods of the time domain are scalar indicators such as RMS, kurtosis, the frequency domain carried the Fourier transform and the cepstrum analysis also the envelope analysis which integrated band pass filtering and Hilbert transform, multi resolution analysis by wavelet transform and Hilbert Huang transform are time-frequency methods [4].

Geometric anomalies that occur due to faulty assembly or improper use are considered bearing defects, and each defective bearing component can be identified by a frequency calculated from its geometric parameters [5].

In addition, decomposition methods such as Local Mean Decomposition (LMD) [6], LMD using empirical optimal envelope (EOE-LMD) [7] and Variational Mode Decomposition (VMD) [8] are used in bearing fault detection approaches. These methods allow the decomposition of vibration signals into several simple components. This is followed by an operation to select the most efficient simple signals containing fault information, using indicators such as the Gini index, which is used to evaluate the number of pulses created by faults [9]. This index performs better than kurtosis, which takes a value of less than three for a healthy bearing and a value of more than three for a failing bearing [9]. Thus, the vibration signal is considered as a convolution product between the impulse part of the signal and the transfer function [10]. Thanks to this, several deconvolution methods have been created to extract the impulse part, such as adaptive maximum cyclostationarity blind deconvolution [11].

This paper presents an approach that incorporates multiple methods to analyze vibration signals and identify the faulty components in the bearing.

2. METHODS

This section introduces an approach that comprises three steps for analyzing bearing vibration signals, as shown in the provided flowchart (Fig.1).

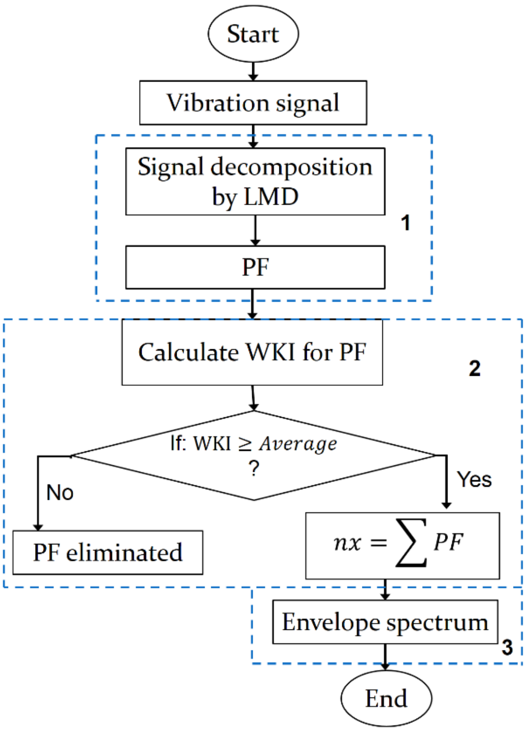

Fig.1 Proposed approach

Localmean decomposition (LMD)

LMD is a method that decomposes a non-stationary signal into a series of PF components. The LMD algorithm can be applied to a given vibration signal $x(t)$and is presented as follows [6]:

- Determination all local extrema (n_i) of the signal $x(t)$, then calculates the local mean (m_i) and the local magnitude (a_i) of each two successive extrema:

$$m_i = \frac{n_i + n_{i+1}}{2} \quad (1)$$

$$a_i = \frac{|n_i - n_{i+1}|}{2} \quad (2)$$

- The moving average method is employed to compute the local mean function $m_{11}(t)$and the envelope estimation function $a_{11}(t)$, which are then subtracted from each other:

$$h_{11}(t) = x(t) - m_{11}(t) \quad (3)$$

- The signal $s_{11}(t)$ is obtained through the division of $h_{11}(t)$by$a_{11}(t)$.

$$s_{11}(t) = \frac{h_{11}(t)}{a_{11}(t)} \quad (4)$$

- The antecedent steps are reiterated for $s_{11}(t)$until the signal $s_{1n}(t)$ reaches complete frequency modulation, and the envelope function is the product of the envelope estimation functions.

$$a_1(t) = a_{11}(t)a_{12}(t)..a_{1n}(t) \quad (5)$$

- The first component (PF1) is acquired through the utilization of the subsequent formula:

$$PF_1(t) = a_1(t)s_{1n}(t) \quad (6)$$

- The residual $u_1(t)$ is acquired by subtracting both the component (PF1) and the initial signal.

$$u_1(t) = x(t) - PF_1(t) \quad (7)$$

- The various steps are reiterated until the residual $u_k(t)$ becomes constant, and ultimately, the signal $x(t)$ is denoted by the subsequent equation:

$$x(t) = \sum_{i=1}^{k} PF_i(t) + u_k(t) \quad (8)$$

Weighted kurtosis index (WKI)

The combination of kurtosis (Ku) and correlation (C) results in WKI, which is intended to pinpoint the component (PF) that responds to defects [12]. The presence of pulses in the signal serves as an indicator of defects, and the degree of similarity between the initial signal and its components is reflected by the correlation measure [12]. The following formula is employed to compute WKI [12]:

$$WKI = ku \times |C| \quad (9)$$

Kurtosis is commonly utilized for diagnosing bearing faults, and it is particularly responsive to pulse signals. When a bearing fails, the kurtosis value increases significantly [13]. In the absence of a defect, the amplitude of the vibration signals approximates a normal distribution, and the kurtosis value is roughly (3) [14].

In your study, the selected components (PF) should demonstrate values above the average WKI value, as indicated by the equation:

$$\begin{cases} if: WKI \geq Average & PF: selected \\ \quad else & PF: \text{removed} \end{cases} \quad (10)$$

Summing up all the chosen components (PF) enables the reconstruction of a new signal $nx(t)$ that comprises multiple pulses and bears a strong resemblance to the initial signal.

$$nx(t) = \sum PF(t) \quad WKI \geq Average \quad (11)$$

Envelope spectrum

The envelope spectrum is commonly used to identify the frequency of defects in bearing components, and it is calculated using the Hilbert and Fourier transforms, as demonstrated in the equations below [15]:

$$H[x(t)] = x(t) * \frac{1}{\pi t} \tag{12}$$

$$E(t) = \sqrt{x(t)^2 + H[x(t)]^2} \tag{13}$$

$$E(f) = \int_{-\infty}^{+\infty} E(t) e^{-j2\pi f t} dt \tag{14}$$

One can examine the relationship between the frequency of peaks and the fault frequencies of bearing components when analyzing the envelope spectrum.
The failure of each component in the bearing defined by a frequency calculated from the geometric parameters as illustrated in the table 1 [16].
z: Number of rolling elements, Dm: Pitch diameter, d: Rolling element diameter, a: Angle of contact, Fr: Operating speed.

Table1 Defect frequency

Components	Formulas
Outer race	$F_{or} = \frac{z \times Fr}{2}\left(1 - \frac{d}{Dm}\cos(a)\right)$
Inner race	$F_{ir} = \frac{z \times Fr}{2}\left(1 + \frac{d}{Dm}\cos(a)\right)$
Cage	$F_{c} = \frac{Fr}{2}\left(1 - \frac{d}{Dm}\cos(a)\right)$
Rolling element	$F_{re} = \frac{Dm \times Fr}{2d}\left(1 - \frac{d^2}{Dm^2}\cos^2(a)\right)$

3. EXPERIMENTAL STUDY

In this section, we analyze the vibration signals of an LDK UER204 bearing type. These signals are available in the XJTU-SY database and are measured using two accelerometers, one mounted on the horizontal axis and the other on the vertical axis, the sampling frequency used is 25.6 kHz [17].
The fault frequencies of the bearing components are determined from the geometric parameters, operating conditions and formulas listed in Table 2 [17].

Table2Faultfrequency values

Operating condition	Geometric parameters	Fault frequency
Speed 35 Hz ***Load 12 kN***	***Outer race diameter 39.8mm*** ***Inner race diameter 29.3mm*** ***Pitch diameter 34.55mm*** ***Number of balls 8*** ***Contact angle 0°***	$F_{or} = 107.9\ Hz$ $F_{ir} = 172.09\ Hz$ $F_c = 13.48\ Hz$ $F_{re} = 72.32\ Hz$

The proposed approach is applied to the vibration signal with an outer ring fault having a fault frequency of 107.9Hz.

Results and discussion

As depicted in figures 2 and 3, the spectrum shape of the vibration signal measured on the horizontal and vertical axis is intricate and challenging to comprehend.

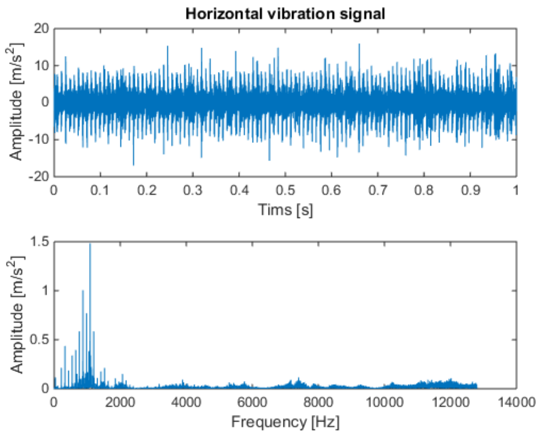

Fig. 2 Horizontal vibration signal

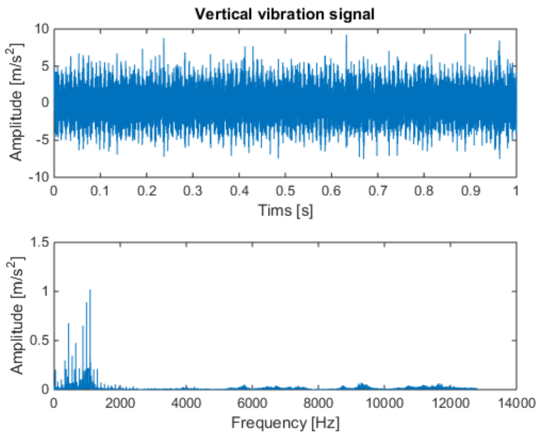

Fig. 3 Vertical vibration signal

Components (PF) represented in figures 4 and 5 were obtained after decomposing the signal using the LMD algorithm.

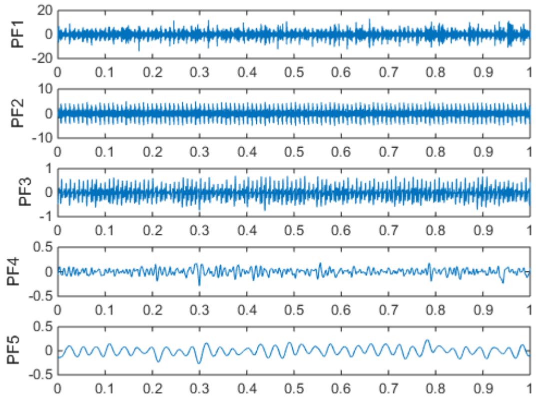

Fig.4 Components of horizontal vibration signal

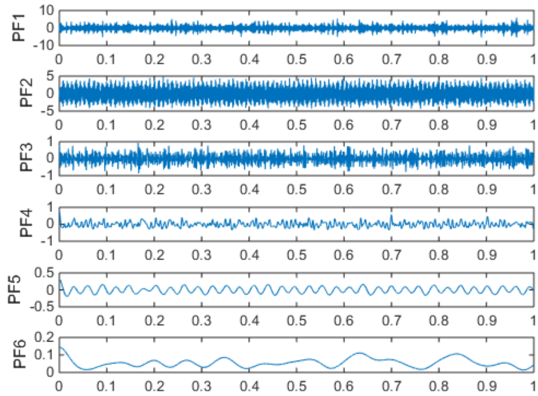

Fig. 5 Components of vertical vibration signal

Based on the values of WKI for each component (PF) listed in Table 3, the new reconstruction signals can be obtained.

For the horizontal vibration signal, the average of the WKI values is 1.84. While for the vertical vibration signal, it is 0.96.

The new reconstruction signal for both the vertical and horizontal cases can be obtained by adding the first and second components:

$$nx(t) = PF_1(t) + PF_2(t) \qquad (15)$$

Table3 WKI values

Components	Vertical vibration signal	Horizontal vibration signal
PF1	*5.27*	*2.47*
PF2	*3.33*	*2.07*
PF3	*0.49*	*0.84*
PF4	*0.07*	*0.23*
PF5	*0.07*	*0.14*
PF6	*0.010*	

The envelope spectrum of the new signals for the horizontal and vertical case shows a high amplitude peak at the outer ring fault frequency 108.9 Hz≅107.9 Hz, as shown in figures 6 and 7.

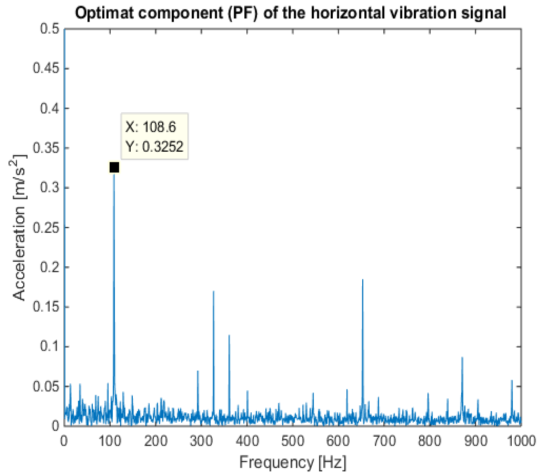

Fig. 6 Envelope spectrum, horizontal case

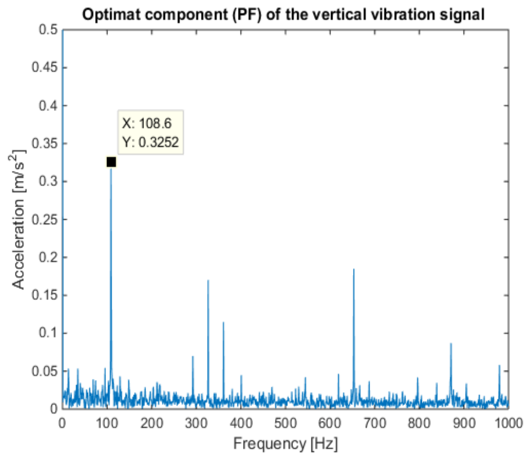

Fig.7 Envelope spectrum, vertical case

4. CONCLUSION

After analyzing the horizontal and vertical vibration signals of the bearing, it was found that the spectral shape of the initial vibration signal is intricate. Therefore, signal processing is vital to enhance the signal quality and achieve a more precise diagnostic outcome.

Decomposing the signal and selecting the optimal components using WKI is a crucial step in reconstructing a new signal that contains many pulses and closely resembles the original signal.

References

[1] Shi, D. F., W. J. Wang, and L. S. Qu. "Defect detection for bearings using envelope spectra of wavelet transform." J. Vib. Acoust. vol.126, no.4, pp.567-573, 2004.

[2] Yu, Dejie, Junsheng Cheng, and Yu Yang. "Application of EMD method and Hilbert spectrum to the fault diagnosis of roller bearings." Mechanical systems and signal processing, vol.19, no.2, pp.259-270, 2005.

[3] Tiboni, Monica, et al. "A review on vibration-based condition monitor- ing of rotating

machinery." Applied Sciences vol.12, no.3, pp.972, 2022.

[4] Li, Wei, et al. "Fault diagnosis of rotating machinery with a novel sta- tistical feature extraction and evaluation method." Mechanical Systems and Signal Processing, vol.50, pp.414-426, 2015.

[5] Dolenc, Bostjan, Pavle Boskoski, and Dani Juricic. "Distributed bearing fault diagnosis based on vibration analysis." Mechanical Systems and Signal Processing. vol.66, pp.521-532, 2016.

[6] Pan, Yubin, et al. "Improved Complete Ensemble Robust Local Mean Decomposition With Adaptive Noise for Slewing Bearings Performance Degradation Assessment." IEEE Access vol.10, pp.78677-78690, 2022.

[7] JIA, Linshan, ZHANG, Qing, ZHENG, Xiang, et al. « The empirical optimal envelope and its application to local mean decomposition." Digital Signal Processing, vol. 87, pp. 166-177, 2019.

[8] Dragomiretskiy, Konstantin, and Dominique Zosso. "Variational mode decomposition." IEEE transactions on signal processing,vol.62, no.3, pp.531-544, 2013.

[9] Albezzawy, Muhammad N., Mohamed G. Nassef, and Nader Sawalhi. "Rolling element bearing fault identification using a novel three-step adaptive and automated filtration scheme based on Gini index." ISA transactions,vol.101, pp.453-460, 2020.

[10] MIAO, Yonghao, ZHANG, Boyao, LIN, Jing, et al. "A review on the application of blind deconvolution in machinery fault diagnosis." Mechanical Systems and Signal Processing, vol.163, pp. 108202, 2022.

[11] WANG, Zhijian, ZHOU, Jie, DU, Wenhua, et al. "Bearing fault diagnosis method based on adaptive maximum cyclostationarity blind deconvolution." Mechanical Systems and Signal Processing, vol.162, pp.108018, 2022.

[12] Dibaj, Ali, et al. "Incipient fault diagnosis of bearings based on parameter-optimized VMD and envelope spectrum weighted kurtosis index with a new sensitivity assessment threshold." ISA transactions, vol.114, pp.413-433, 2021.

[13] Wang, Zhijian, et al. "A novel fault diagnosis method of gearbox based on maximum kurtosis spectral entropy deconvolution." IEEE Access, vol.7, pp.29520-29532, 2019.

[14] Bouaouiche, Karim, Yamina Menasria, and Dalila Khalfa. "Bearing fault detection using a method involving absolute value spectrum and impulsivity evaluation." Diagnostyka, vol.25, no.2, 2024.

[15] Bouaouiche, Karim, Yamima Menasria, and Dalila Khalifa. "Detection of defects in a bearing by analysis of vibration signals." Diagnostyka vol.24, no.02, pp.1-7, 2023.

[16] Bouaouiche, Karim, Yamina Menasria, and Dalila Khalfa. "Diagnosis of rotating machine defects by vibration analysis." Acta IMEKO vol.12, no.1, pp.1-6, 2023.

[17] XJTU-SY Bearing database. Online[Accessed 24/12/ 2023]https://biaowang.tech/xjtu-sy-bearing-datasets/