Journal of Signal and Information Processing, 2023, 14, 9-24
https://www.scirp.org/journal/jsip
ISSN Online: 2159-4481
ISSN Print: 2159-4465

Adaptive Variational Mode Decomposition for Bearing Fault Detection

Xing Xing[1], Ming Zhang[2], Wilson Wang[3*]

[1]Electrical and Computer Engineering, Lakehead University, Thunder Bay, Canada
[2]Automotive Engineering, Weifang College of Engineering, Qingzhou, China
[3]Mechanical Engineering, Lakehead University, Thunder Bay, Canada
Email: *wilson.wang@Lakeheadu.ca

How to cite this paper: Xing, X., Zhang, M. and Wang, W. (2023) Adaptive Variational Mode Decomposition for Bearing Fault Detection. *Journal of Signal and Information Processing*, **14**, 9-24.
https://doi.org/10.4236/jsip.2023.142002

Received: May 17, 2023
Accepted: May 28, 2023
Published: May 31, 2023

Abstract

Rolling element bearings are commonly used in rotary mechanical and electrical equipment. According to investigation, more than half of rotating machinery defects are related to bearing faults. However, reliable bearing fault detection still remains a challenging task, especially in industrial applications. The objective of this work is to propose an adaptive variational mode decomposition (AVMD) technique for non-stationary signal analysis and bearing fault detection. The AVMD includes several steps in processing: 1) Signal characteristics are analyzed to determine the signal center frequency and the related parameters. 2) The ensemble-kurtosis index is suggested to decompose the target signal and select the most representative intrinsic mode functions (IMFs). 3) The envelope spectrum analysis is performed using the selected IMFs to identify the characteristic features for bearing fault detection. The effectiveness of the proposed AVMD technique is examined by experimental tests under different bearing conditions, with the comparison of other related bearing fault techniques.

Keywords

Bearing Fault Detection, Vibration Signal Analysis, Intrinsic Mode Functions, Variational Mode Decomposition

1. Introduction

Rotating machines are commonly used in almost every aspect of people's daily lives such as vehicles, motors, turbines, and robots. Failures of a rotating machine may result in reduced production quality, degraded safety, increased costs in repairs and maintenance, or even potential risk of loss of life [1]. Rolling element bearings, which are referred to as bearings thereafter, are essential components in rotating machinery to support rotating shafts and reduce frictions. Based on investigation [2], up to 75% of imperfections in small- and medium-size rotating machines, and 50% of imperfections in large-size rotating machines, are related to bearing faults. Therefore, a reliable and effective bearing fault detection technology is critically needed in industries to identify a bearing defect at its earliest stage so as to prevent machine performance degradation, increase safe and productivity, and reduce maintenance costs.

Reliable bearing fault detection still remains a challenging task in this research, in real-world applications. Different from a gear or a shaft, a rolling element bearing is a system consisting of components such as the rotating ring, fixed ring, rolling elements, and a cage. Signal characteristics could be non-stationary especially when faults occur in rolling elements or rotating races of bearings [1]. Another challenge lies in signal modulation. Bearing signals are relatively weak and are usually modulated by other strong vibrations generated by gear meshing, which makes it more difficult to identify the characteristic frequencies associated with a bearing fault [3]. Moreover, bearing fault symptoms can vary widely depending on the specifics of the fault type, defect location, and operating conditions such as bearing load and speed. These limitations present a significant challenge in developing a reliable and robust bearing detection technique especially for real-world industrial applications.

The most common method used in bearing fault detection is based on Fourier transform (FT) spectral analysis. If the geometric parameters of a bearing are known, theoretical characteristic frequencies of bearing faults can be calculated, with fault detection performed by examining health-related characteristic frequency components on the spectrogram [3]. To address non-stationary in signals, time-frequency analysis methods have been commonly used. These methods can decompose the complex structure of signals and provide direct information about the frequency components occurring over time [4]. Common time-frequency analysis methods include the short-time FT [5], Wigner-Ville distribution [6], wavelet transform [7], wavelet packet analysis, and Hilbert-Huang transform (HHT) [8]. However, each method has its own advantages and limitations in practical processing applications. For instance, the short-time FT may not provide valid information including simultaneous time and frequency localization. The Wigner-Ville and other bilinear time-frequency distributions in bearing fault detection are limited due to potential cross-interference items [9]. The wavelet transform is inefficient for processing signals whose energy is not well concentrated in the frequency domain [10]. On the other hand, in HHT analysis, empirical mode decomposition (EMD) is a self-adaptive method for non-stationary signal analysis [11], but it has limitations in mode mixing, over envelope, or under envelope, which can affect the processing accuracy [12].

Variational mode decomposition (VMD) is a relatively new method of signal decomposition, which has been studied and applied in the field of signal processing in recent years [13]. The VMD decomposes the original signal into several sub-signals with different center frequencies in the framework of a variational model. Its essence can be seen as a set of adaptive Wiener filters [14]. Although VMD has been used in the extraction of fault signal features [15] [16] [17], it still has some clear drawback, or it requires setting up the number of modes and the bandwidth control parameters in advance. Most of the research works have focused on how to improve its adaptability and parameter optimization. For example, a prediction test method is proposed in [18] to make the decomposition prediction by adaptively changing the related algorithm parameters; however, it is an empirical method and could be difficult to be implemented in bearing fault detection applications [18]. Li *et al.* have proposed an independence-oriented VMD on the basis of the spectrum distribution to detect wheel set-bearing faults [19]. However, this method is limited by the complexity of the signal and suffers from possible over-decomposition. Moreover, the particle swarm optimization is used in [20] to optimize the VMD parameters, but the inappropriate ratio between the average value and the variance could generate the loss of impact component information in the original signal. In addition, several optimization algorithms have been proposed in [21] [22] [23] to optimize the number of modes for VMD analysis in specific engineering scenarios. However, these optimization algorithms still have some problems, including complex optimization model, slow convergence of parameter determination, and easy falling into local optimization.

To tackle the aforementioned challenge in the available VMD methods, an adaptive VMD (*i.e.*, AVMD in short) technique is proposed in this paper for signal property analysis and bearing fault detection. Firstly, the intrinsic mode functions (IMFs) are decomposed from the original signal, and IMF number is determined under a certain target setting and the close correlation between each IMF and the original input signal. Secondly, the ensemble-kurtosis index is suggested to select the most representative IMFs to decompose the target signal. Thirdly, the envelope spectrum analysis is performed using the selected IMFs to recognize the representative features for bearing fault detection.

The remainder of the paper is organized as follows: Firstly the general VMD method is briefly discussed in Section 2. The proposed AVMD technique and its implementation are discussed in Section 3. The AVMD effectiveness is examined in Section 4 by experimental tests. The conclusions of this paper are summarized in Section 5.

2. Discussion of the VMD Method

In VMD analysis, it is assumed that the original signal can be decomposed into several modes, and each mode is a signal with a narrow-band and located around a center frequency [14]. The IMF, $u_k(t)$, represents an amplitude-modulated and frequency-modulated signal, which can be expressed as:

$$u_k(t) = A_k(t) \times \cos(\phi_k(t)) \tag{1}$$

where k represents the k-th IMF; $A_k(t)$ denotes the instantaneous amplitude; $\phi_k(t)$ denotes the phase.

The fundamental operation of VMD can be expressed by solving the constrained variational problem in Equation (2):

$$\begin{gathered}\min_{\{u_k\},\{\omega_k\}}\left\{\sum_{k=1}^{K}\left\|\partial_t\left[\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t)\right]\mathrm{e}^{-j\omega_k t}\right\|_2^2\right\}\\ \text{s.t. } \sum_{k=1}^{K}u_k(t)=f(t)\end{gathered}\tag{2}$$

where K is the number of IMFs; u_k and ω_k denote the k-th IMF and its corresponding center frequency; ∂_t denotes the partial derivative of time; $\delta(t)$ is the Dirac delta distribution; $f(t)$ is the original input signal; j is the complex number; * is the convolution operator.

To solve the constrained variation problem of Equation (2), the augmented Lagrangian method [24] can be used to covert Equation (2) into an unconstrained optimization problem, which can be rewritten as:

$$\begin{aligned}\mathcal{L}\left(\{u_k\},\{\omega_k\},\lambda\right)&:=\alpha\sum_k\left\|\partial_t\left[\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t)\right]\mathrm{e}^{-j\omega_k t}\right\|_2^2\\&+\left\|f(t)-\sum_k u_k(t)\right\|_2^2+\left\langle\lambda(t),f(t)-\sum_k u_k(t)\right\rangle\end{aligned}\tag{3}$$

where α is the quadratic penalty factor and λ is Lagrangian multiplier coefficient.

In order to obtain an optimal solution to the unconstrained problem in Equation (3), an alternated direction method of multipliers can be used for analysis [24]. The unconstrained problem in Equation (3) can be transferred into two equivalent minimization problems based on alternated direction method of multipliers. Thus, modes u_k and their corresponding center frequency ω_k can be updated (*i.e.*, from step n to step $n+1$) as:

$$u_k^{n+1}\leftarrow\arg\min_{u_k}\mathcal{L}\left(\left\{u_{i<k}^{n+1}\right\},\left\{u_{i\ge k}^{n}\right\},\left\{\omega_i^n\right\},\lambda^n\right)\tag{4}$$

$$\omega_k^{n+1}\leftarrow\arg\min_{\omega_k}\mathcal{L}\left(\left\{u_i^{n+1}\right\},\left\{\omega_{i<k}^{n+1}\right\},\left\{\omega_{i\ge k}^{n}\right\},\lambda^n\right)\tag{5}$$

Based on Equation (4), the equivalent minimization problem can be represented as:

$$\begin{aligned}u_k^{n+1}=\arg_{u_k\in X}\min\Bigg\{&\alpha\left\|\partial_t\left[\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t)\right]\mathrm{e}^{-j\omega_k t}\right\|_2^2\\&+\left\|f(t)-\sum_i u_i(t)+\frac{\lambda(t)}{2}\right\|_2^2\Bigg\}\end{aligned}\tag{6}$$

Using Parseval/Plancherel Fourier isometry under the L^2 norm and the Hermitian symmetry of the FT of the signal, Equation (6) can be solved in the spectrum domain, such that:

$$\hat{u}_k^{n+1} = \arg_{\hat{u}_k, u_k \in X} \min \left\{ \int_0^\infty 4\alpha (\omega - \omega_k)^2 \left| \hat{u}_k(\omega) \right|^2 + 2 \left| \hat{f}(\omega) - \sum_i \hat{u}_i(\omega) + \frac{\hat{\lambda}(\omega)}{2} \right|^2 \mathrm{d}\omega \right\} \quad (7)$$

After the first variation of the positive frequency vanishes, the solution to this quadratic optimization problem becomes:

$$\hat{u}_k^{n+1}(\omega) = \frac{\hat{f}(\omega) - \sum_{i \neq k} \hat{u}_i(\omega) + \frac{\hat{\lambda}(\omega)}{2}}{1 + 2\alpha (\omega - \omega_k)^2} \quad (8)$$

which can be considered as a Wiener filter to process current residual [25].

In addition, from Equation (5), the updated reconstruction term of center frequency ω_k becomes:

$$\omega_k^{n+1} = \arg_{\omega_k} \min \left\{ \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] \mathrm{e}^{-j\omega_k t} \right\|_2^2 \right\} \quad (9)$$

Similarly, the optimization of the center frequency can also be performed in the frequency domain, by optimization the following function:

$$\omega_k^{n+1} = \arg_{\omega_k} \min \left\{ \int_0^\infty (\omega - \omega_k)^2 \left| \hat{u}_k(\omega) \right|^2 \mathrm{d}\omega \right\} \quad (10)$$

This quadratic optimization problem can be solved by:

$$\omega_k^{n+1} = \frac{\int_0^\infty \omega \left| \hat{u}_k(\omega) \right|^2 \mathrm{d}\omega}{\int_0^\infty \left| \hat{u}_k(\omega) \right|^2 \mathrm{d}\omega} \quad (11)$$

Moreover, the Lagrangian multiplier $\lambda(t)$ can be updated by:

$$\hat{\lambda}^{n+1} = \hat{\lambda}^n(\omega) + \tau \left(\hat{f}(\omega) - \sum_k \hat{u}_k^{n+1}(\omega) \right) \quad (12)$$

where τ is the iteration step size.

The iteration will be completed until the accuracy meets the following convergence criterion:

$$\sum_k \left\| \hat{u}_k^{n+1} - \hat{u}_k^n \right\|_2^2 \Big/ \left\| \hat{u}_k^n \right\|_2^2 < \varepsilon \quad (13)$$

where ε is the convergence threshold used to control the reconstruction of each mode.

In processing, the steps of the VMD algorithm are summarized as follows:

Step 1: Initialize $\{\hat{u}_k^1\}$, $\{\omega_k^1\}$, $\hat{\lambda}^1$, and $n = 1$.

Step 2: Calculate $\hat{u}_k$ and ω_k using Equations (8) and (11), respectively, $k = 1, 2, \cdots, K$.

Step 3: Update $\hat{\lambda}$ in Equation (12).

Step 4: Repeat Steps 2 - 3 until the iteration meets the criterion in Equation (13).

Step 5: Compute the K mode components u_k.

The parameters K, α, τ, and ε need to be selected based on applications through error and trial procedures. $\tau = 0$, $\varepsilon = 1$ are can be selected in this case for general processing applications.

3. The Proposed AVMD Technique

The proposed AVMD aims to solve the problem of VMD parameter adaption and further expand its application in bearing fault diagnosis. First, the details of the relevant methods for determining the VMD parameters will be presented in this section. Then, the process of AVMD will be discussed.

3.1. Cross-Correlation

Before VMD decomposition, the parameter K (*i.e.*, IMF number) needs to be selected properly. If K is too small, extra signal components may appear in one mode at the same time or some components become unpredictable. Conversely, if K is too large, some components will appear in more than one mode and the frequencies of the modal centers will overlap [26]. Therefore, choosing a suitable K value is important in VMD processing to improve the accuracy of the decomposed modes. The K value is usually selected by experience or by trial and error.

In proposed AVMD, K will be determined by the correlation between the input signal and decomposed modes. In signal processing, cross-correlation is a measure of similarity between two or more time series data sets. Accordingly, the correlation between the original input signal and sum of the decomposed modes can be calculated by

$$\rho_{xy} = \frac{C_{xy}}{\sigma_x \sigma_y} \tag{14}$$

where x is the sum of the modes; y is the original signal; C_{xy} is the cross-covariance function; σ_x and σ_y are the standard deviations of x and y, respectively. The cross-correlation ρ_{xy} represents the correlation between the integration of the decomposed modes and the original signal; the larger ρ_{xy}, the higher the correlation between two signals.

3.2. Determination of the Penalty Factor

Based on the discussion in Section 2 and literature [14], the function of the penalty factor α can be used to determine the bandwidth of mode component. In general, a constant penalty factor can be selected and used in VMD mode decomposition. Generally, a larger penalty factor will generate the narrower bandwidth of the mode component; conversely, a smaller penalty factor will result in a wider the bandwidth of the mode component. According to the characteristics of the spectrum distribution of a vibration signal, most bearing fault characteristic frequencies and their harmonics are located over the low and medium frequency region [25]. Therefore, in the proposed AVMD technique, the characteristics of the signal's center frequency will be used to determine the penalty factor corresponding to each mode so as to determine the penalty factor adaptively. The detail of how to adaptively select penalty factors will be discussed below.

When the center frequency of the decomposed mode is low, the mode components are mainly harmonics in the low and medium frequency bandwidths; then a larger penalty factor will be chosen, and vice versa [27]. Equation (15) is an empirical formula that can be used to adaptively determine the penalty factor:

$$\alpha_k = \left(\frac{1}{1 + e^{\log_{10} \frac{2 f_{kc}}{f_s}}} - 0.5 \right) \cdot \frac{f_s}{2} \tag{15}$$

where α_k is the penalty factor and f_{kc} is the center frequency of the k-th mode component, respectively; f_s is the sampling frequency. f_{kc} can be calculated by

$$f_{kc} = \frac{\sum_{i=1}^{N/2} \left[i \cdot f_s / N \cdot \left| U_k(i) \right|^2 \right]}{\sum_{i=1}^{N/2} \left| U_k(i) \right|^2} \tag{16}$$

where N is the length of the original signal, and U_k is the discrete FT of k-th mode component u_k.

By using Equation (16), the penalty factor α_k can be adaptively adjusted according to the frequency characteristics of each decomposed mode.

3.3. Ensemble Kurtosis

In the proposed AVMD, after mode decomposition, the next step is to select proper IMFs for signal analysis. In bearing fault detection, fault characteristic frequencies, harmonics, impulses, and noise have different probability densities and statistical properties. Kurtosis is a measure of the tails of the probability distribution function [25]. In literature, kurtosis-based methods tend to focus on the frequency band of individual pulses only, rather than on the defect impulses, because these methods mainly emphasize impulsivity but ignore the cyclicity. Envelope spectral kurtosis can measure and evaluate the cyclicity [25], which will be adopted in bearing fault diagnosis in this work such that:

$$E_K = E_{KS} \cdot K_u = \frac{\sum_{p=1}^{P} \left| \overline{S_E}(p) \right|^4}{\left(\sum_{p=1}^{P} \left| \overline{S_E}(p) \right|^2 \right)^2} \cdot K_u \tag{17}$$

where E_K is the ensemble kurtosis; E_{KS} is envelope spectrum kurtosis; K_u is the kurtosis; S_E is the envelope spectrum of signal and P is the sampling number of envelope spectrum. From our primary investigation, it is shown that E_K index is sensitive to impulses, which will be used in this work for the selection of IMFs for signal analysis and bearing fault detection.

3.4. Implementation of the Proposed AVMD

The proposed AVMD technique will be used to extract the impulsive features for bearing fault detection. Its processing flowchart is presented in **Figure 1**. The main steps of the AVMD are summarized as follows:

Step 1: Initialize system parameters: $K = 1$ and $\alpha = 100$.

Step 2: Run the VMD decomposition and compute the correlation using

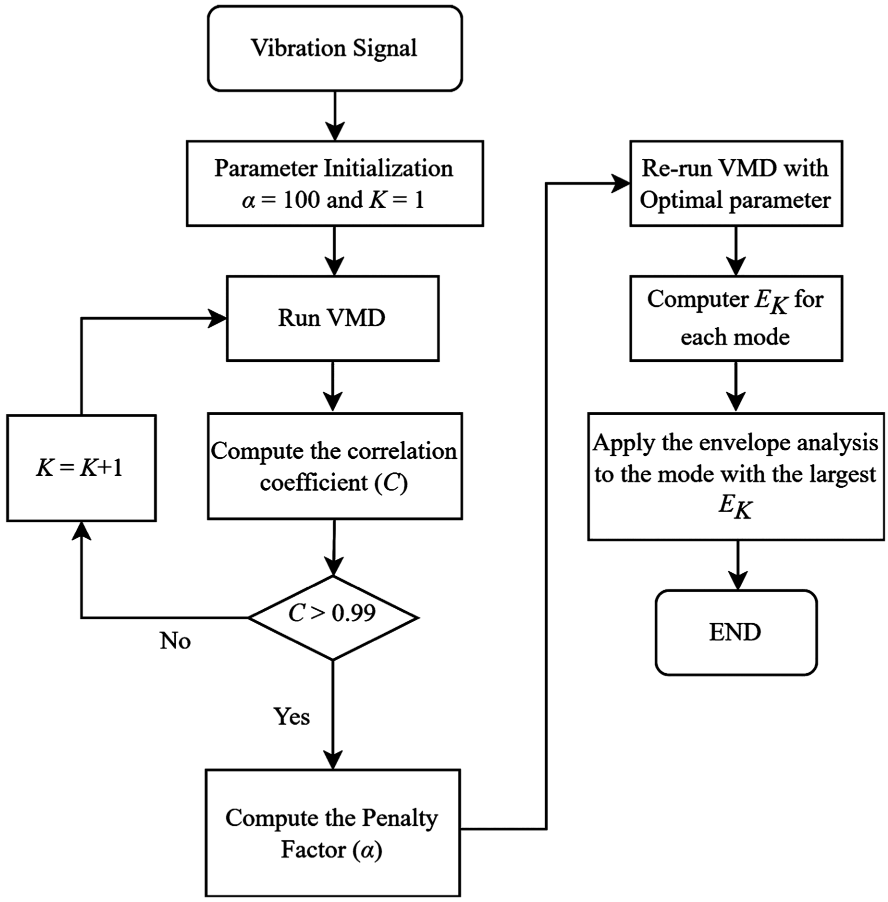

Figure 1. The flowchart of proposed AVMD technique.

Equation (14). If the correlation is over 99%, proceed to Step 3. Otherwise, let $K := K + 1$ and repeat Step 2.

Step 3: Compute the penalty factor using Equation (15) for each mode.

Step 4: Re-run VMD decomposition using the updated K and α; compute E_K using Equation (17) for each mode.

Step 5: Analyze the largest E_K mode by the envelope analysis and do bearing fault detection.

4. Experimental Tests and Results Analysis

The effectiveness of the proposed AVMD technique is examined experimentally in this section. Figure 2 shows the experimental setup used in this test. It is driven by a 3 HP induction motor with a speed range of 100 - 4200 rpm, controlled by a frequency converter (VFD022B21A). An elastic coupler is applied to eliminate high frequency vibrations generated by the motor. An optical sensor is used to provide a signal of one pulse per revolution to measure shaft speed. The accelerometer (ICP-603C01) is mounted on top of the bearing to measure the vibration signal along the vertical axis. The tested bearing (MBER-10K) located on the left side of the housing is used for the test. The static bearing load is provided by two heavy mass discs and dynamic load is provided by a break system through a belt-drive.

In this experiment, four bearing health conditions are considered for testing: a healthy bearing, a bearing with outer race fault, a bearing with inner race fault, and a bearing with rolling element defect. The tested bearings have the following parameters: the number of rolling elements: 8, rolling element diameter: 7.938 mm, pitch diameter: 33.503 mm, and the angle of contact: 0 degree. A set of processing results from tests with 1800 rpm motor speed (or $f_r = 30$ Hz) and medium load level are used for illustration. The sampling frequency is 32,000 Hz, and the length of the signal is 100,000. Table 1 summarizes the characteristic frequencies in terms of shaft speed f_r Hz. For comparison, the test results of proposed AVMD method will compare the Hilbert-Huang transform (HHT) [8] and the Teager-Huang transform (THT) [28]. All the techniques are implemented in MATLAB 2022a.

Figure 3 shows processing results using the related techniques, for the health bearing with characteristic frequency $f_H = 30$ Hz. The AVMD is applied with $K = 4$ and penalty factor $\alpha_k = 1216$ calculated using Equation (15).

In this case, although all the related techniques can recognize the healthy bearing characteristic frequency and its few harmonics, the AVMD technique can provide the most noticeable diagnostic results with the highest magnitude compared with other two techniques.

Figure 4 shows the processing results for a bearing with outer-race damage

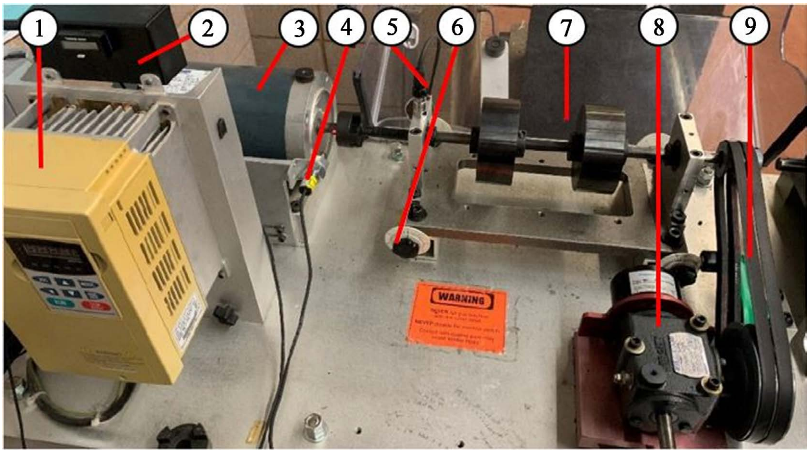

Figure 2. Experimental setup: (1) speed control; (2) encoder display; (3) drive motor; (4) optical encoder; (5) ICP accelerometer; (6) misalignment adjustor; (7) adjustable rig; (8) variable load system; (9) belt drive.

Table 1. Experiment setup bearing fault frequency in terms of shaft speed f_r Hz.

Bearing Health Condition	Characteristic Frequency (Hz)
Healthy bearing	$f_H = f_r$
Outer race fault	$f_{od} = 3.052 \times f_r$
Inner race fault	$f_{id} = 4.947 \times f_r$
Rolling element fault	$f_{bd} = 3.983 \times f_r$

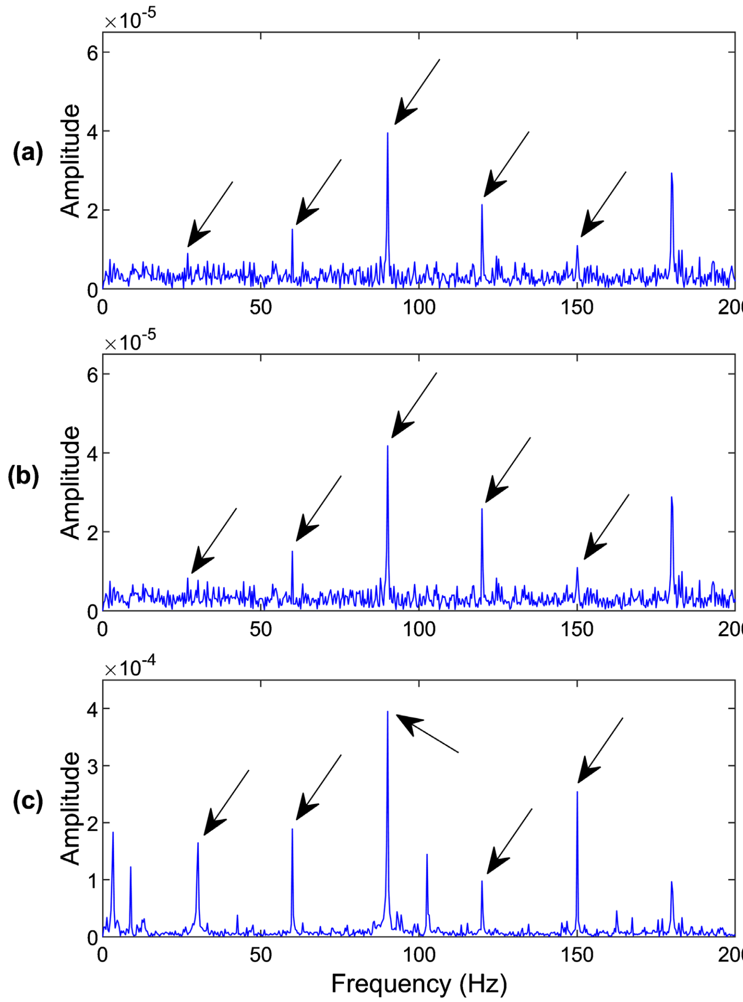

Figure 3. Processing results for a healthy bearing using the related techniques: (a) HHT, (b) THT, (c) AVMD. f_H = 30 Hz. Arrows specify characteristic frequency and its harmonics.

with a characteristic frequency f_{od} = 90.9 Hz. In this case, the AVMD technique uses K = 5 and penalty factor α_k = 1216.

In this case, all the related techniques can recognize the outer race bearing fault characteristic frequency f_{od} = 90.9 Hz and its first few harmonics. This is because when the bearing outer race is damaged; the generated impulses and features are time-invariant, which are relatively easy to determine using general vibration-based fault detection techniques. In this case, however, the fundamental characteristic frequency (f_{od} = 90.9 Hz) using the HHT in Figure 4(a) and the THT in Figure 4(b) is lower than an adjacent component in magnitude, which may generate false diagnostic result especially in automatic bearing health monitoring. On the other hand, the proposed AVMD technique can effectively suppress noise and predict the occurrence of outer race defect as demonstrated in Figure 4(c).

Figure 5 shows the processing results using the related techniques for a bearing with inner race defect, with the characteristic frequency f_{id} = 147.9 Hz. In

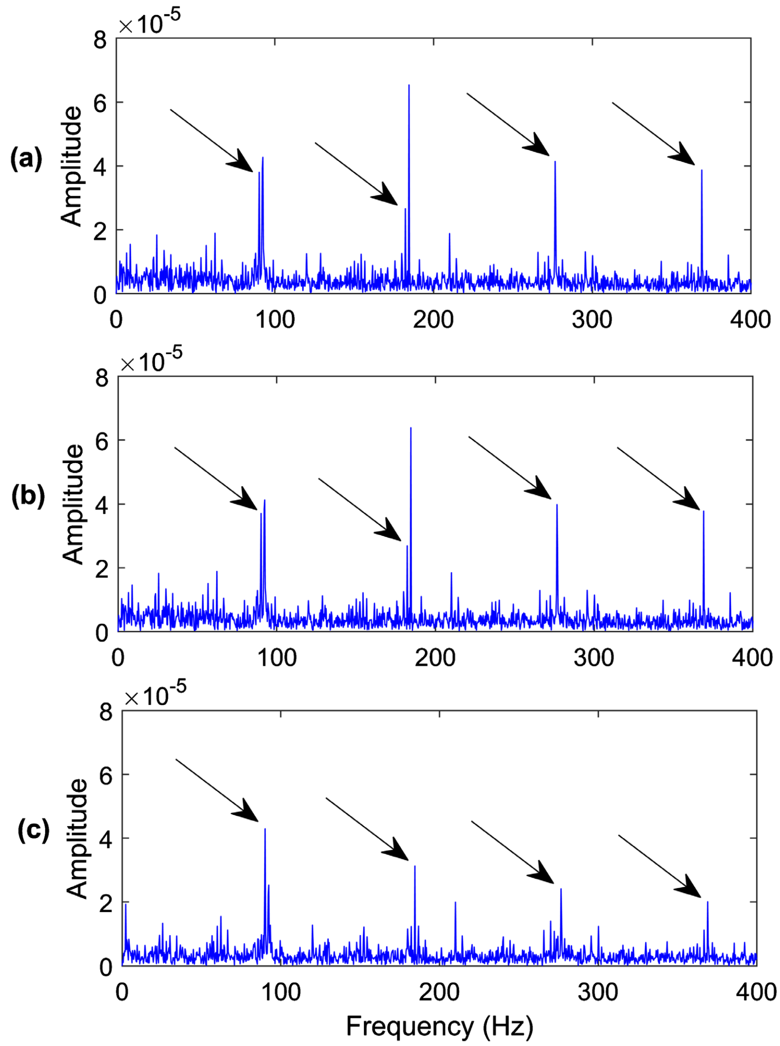

Figure 4. Processing results for an outer-race damaged bearing using the related techniques: (a) HHT, (b) THT, (c) AVMD. f_{od} = 90.9 Hz. Arrows specify characteristic frequency and its harmonics.

this case, the AVMD uses $K = 5$ and penalty factor $\alpha_k = 1304$.

In comparison of the HHT in Figure 5(a), the THT technique in Figure 5(b) provides better performance with clear fault detection with the domain fault characteristic frequency (f_{id} = 147.9 Hz) due to the advantage of Teager operator in signal demodulation. On the other hand, the proposed AVMD technique in Figure 5(c) outperforms even the THT with a higher resolution, and can provide better fault diagnostic accuracy due to its efficient frequency suppression.

Figure 6 depicts the processing results for a bearing with the rolling element damage. The theoretical characteristic frequency is f_{bd} = 91.57 Hz. The AVMD has parameters of $K = 5$ and penalty factor $\alpha_k = 284$.

In this case, none of these three techniques can provide clear fault detection results. In general, fault detection in a rolling element is a challenging task as the representative features could be time-varying. Both the HHT in Figure 6(a) and THT in Figure 6(b) have failed to identify the characteristic fault frequency (f_{bd}

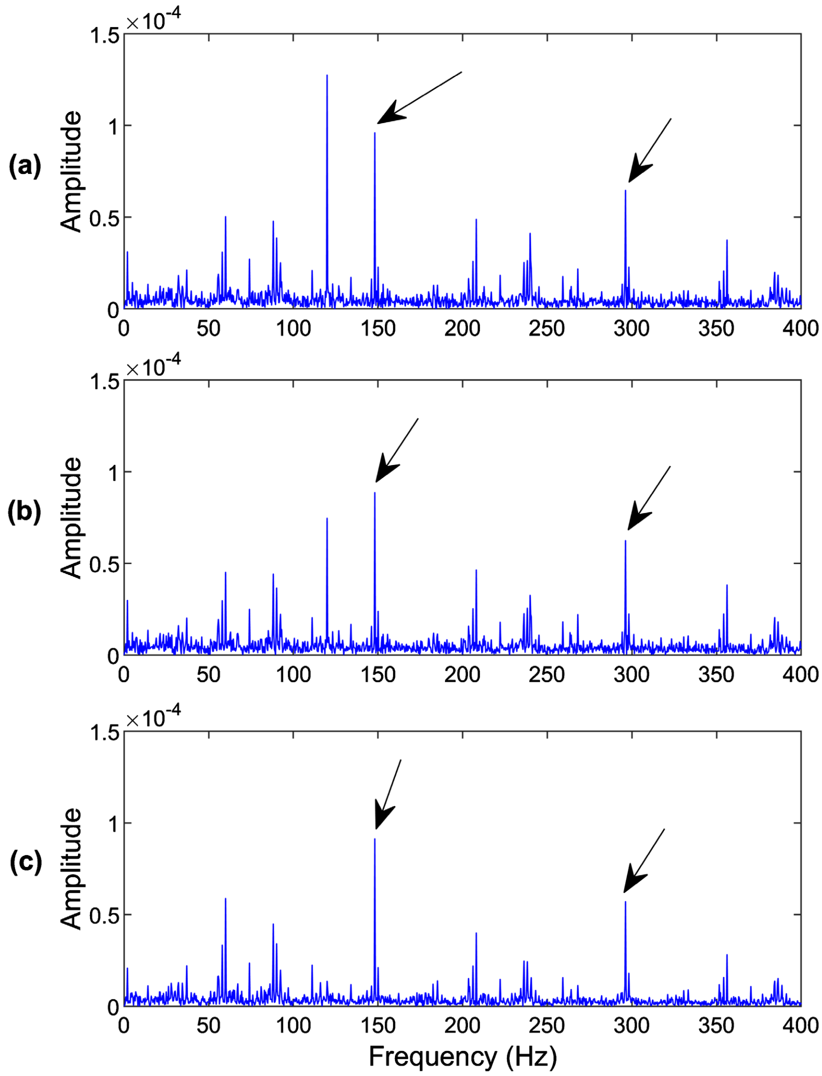

Figure 5. Processing results for an inner-race damaged bearing using the related techniques: (a) HHT, (b) THT, (c) AVMD. f_{id} = 147.9 Hz. Arrows specify characteristic frequency and its harmonics.

= 91.57 Hz). The AVMD is the only technique that can recognize the fundamental fault characteristic frequency in Figure 6(c) in this case, even though it is not the dominant frequency component in the spectral map.

5. Conclusion

A new AVMD technique has been proposed in this work for nonlinear signal analysis and bearing fault detection. The AVMD takes several procedures in signal processing: 1) The VMD decomposition is undertaken to compute the correlation between the original signal and the synthesis of the decomposed modes. 2) The penalty factor is determined analytically for each mode. 3) Ensemble kurtosis is computed for each mode. 4) The most representative modes are selected, and the corresponding envelope analysis is undertaken for bearing fault detection. The effectiveness of the proposed AVMD technique is verified by

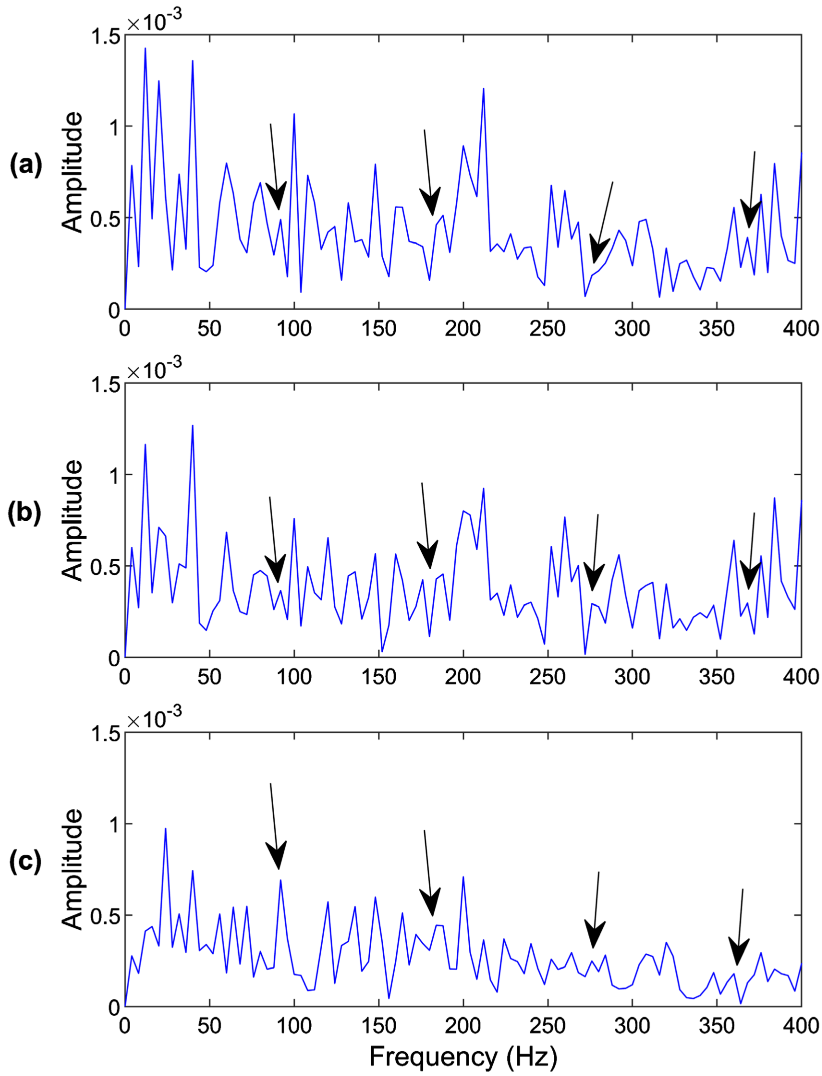

Figure 6. Processing results for a rolling-element damaged bearing using the related techniques: (a) HHT, (b) THT, (c) AVMD. f_{bd} = 91.57 Hz. Arrows specify characteristic frequency and its harmonics.

experimental tests under different bearing health and operating conditions. The test results have shown that the proposed AVMD technique can properly de-noise the signal and highlight the fault-related features for bearing fault detection. It outperforms the related techniques under these controlled testing conditions. It has the potential to be applied for fault detection of bearings in rotating machines. Advanced research is undertaken to adaptively optimize the related parameters in the AVMD algorithm and to improve its accuracy to predict the defects occurring on the inner ring and rolling elements.

Acknowledgements

This work was supported in part by the Natural Sciences and Engineering Research Council of Canada (NSERC) and the Bare Point Water Treatment Plant in Thunder Bay, ON, Canada.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Neupane, D. and Seok, J. (2020) Bearing Fault Detection and Diagnosis Using Case Western Reserve University Dataset with Deep Learning Approaches: A Review. *IEEE Access*, **8**, 93155-93178. https://doi.org/10.1109/ACCESS.2020.2990528

[2] Thomson, W.T. and Fenger, M. (2001) Current Signature Analysis to Detect Induction Motor Faults. *IEEE Industry Applications Magazine*, **1**, 26-34. https://doi.org/10.1109/2943.930988

[3] Nandi, S., Toliyat, H.A. and Li, X. (2005) Condition Monitoring and Fault Diagnosis of Electrical Motors—A Review. *IEEE Transactions on Energy Conversion*, **20**, 719-729. https://doi.org/10.1109/TEC.2005.847955

[4] Sejdic, E., Djurovic, I. and Jiang, J. (2009) Time-Frequency Feature Representation Using Energy Concentration: An Overview of Recent Advances. *Digital Signal Processing*, **19**, 153-183. https://doi.org/10.1016/j.dsp.2007.12.004

[5] Cocconcelli, M., Zimroz, R., Rubini, R. and Bartelmus, W. (2012) STFT Based Approach for Ball Bearing Fault Detection in a Varying Speed Motor. In: Fakhfakh, T., Bartelmus, W., Chaari, F., Zimroz, R. and Haddar, M., Eds., *Condition Monitoring of Machinery in Non-Stationary Operations*, Springer, Berlin, 41-50. https://doi.org/10.1007/978-3-642-28768-8_5

[6] Lee, J.H., Kim, J. and Kim, H.J. (2001) Development of Enhanced Wigner-Ville Distribution Function. *Mechanical Systems and Signal Processing*, **15**, 367-398. https://doi.org/10.1006/mssp.2000.1365

[7] Yang, Y., Yu, D. and Cheng, J. (2006) A Roller Bearing Fault Diagnosis Method Based on EMD Energy Entropy and ANN. *Journal of Sound and Vibration*, **294**, 269-277. https://doi.org/10.1016/j.jsv.2005.11.002

[8] Huang, N. *et al.* (1998) The Empirical Mode Decomposition and the Hilbert Spectrum for Nonlinear and Non-Stationary Time Series Analysis. *Physical and Engineering Sciences*, **454**, 903-995. https://doi.org/10.1098/rspa.1998.0193

[9] Zhang, X., Liu, Z., Miao, Q. and Wang, L. (2018) Bearing Fault Diagnosis Using a Whale Optimization Algorithm-Optimized Orthogonal Matching Pursuit with a Combined Time-Frequency Atom Dictionary. *Mechanical Systems and Signal Processing*, **107**, 29-42. https://doi.org/10.1016/j.ymssp.2018.01.027

[10] Peng, Z.K., Tse, P.W. and Chu, F.L. (2005) A Comparison Study of Improved Hilbert–Huang Transform and Wavelet Transform: Application to Fault Diagnosis for Rolling Bearing. *Mechanical Systems and Signal Processing*, **19**, 974-988. https://doi.org/10.1016/j.ymssp.2004.01.006

[11] Gao, J. and Shang, P. (2019) Analysis of Complex Time Series Based on EMD Energy Entropy Plane. *Nonlinear Dynamics*, **96**, 465-482. https://doi.org/10.1007/s11071-019-04800-5

[12] Zhang, X., Miao, Q., Zhang, H. and Wang, L. (2018) A Parameter-Adaptive VMD Method Based on Grasshopper Optimization Algorithm to Analyze Vibration Signals from Rotating Machinery. *Mechanical Systems and Signal Processing*, **108**, 58-72. https://doi.org/10.1016/j.ymssp.2017.11.029

[13] Song, Q., Jiang, X., Wang, S., Guo, J., Huang, W. and Zhu, Z. (2022) Self-Adaptive Multivariate Variational Mode Decomposition and Its Application for Bearing Fault

Diagnosis. *IEEE Transactions on Instrumentation and Measurement*, **71**, 1-13. https://doi.org/10.1109/TIM.2021.3139660

[14] Dragomiretskiy, K. and Zosso, D. (2014) Variational Mode Decomposition. *IEEE Transactions on Signal Processing*, **62**, 531-544. https://doi.org/10.1109/TSP.2013.2288675

[15] Wang, Y. and Markert, R. (2016) Filter Bank Property of Variational Mode Decomposition and Its Applications. *Signal Processing*, **120**, 509-521. https://doi.org/10.1016/j.sigpro.2015.09.041

[16] Jiang, X., Li, S. and Cheng, C. (2016) A Novel Method for Adaptive Multiresonance Bands Detection Based on VMD and Using MTEO to Enhance Rolling Element Bearing Fault Diagnosis. *Shock Vibration*, **2016**, Article ID: 8361289. https://doi.org/10.1155/2016/8361289

[17] Wang, Y., Markert, R., Xiang, J. and Zheng, W. (2015) Research on Variational Mode Decomposition and Its Application in Detecting Rub-Impact Fault of the Rotor System. *Mechanical Systems and Signal Processing*, **60-61**, 243-251. https://doi.org/10.1016/j.ymssp.2015.02.020

[18] Sahani, M. and Dash, P.K. (2021) Deep Convolutional Stack Autoencoder of Process Adaptive VMD Data with Robust Multikernel RVFLN for Power Quality Events Recognition. *IEEE Transactions on Instrumentation and Measurement*, **70**, 1-12. https://doi.org/10.1109/TIM.2021.3054673

[19] Li, Z., Chen, J., Zi, Y. and Pan, J. (2017) Independence-Oriented VMD to Identify Fault Feature for Wheel Set Bearing Fault Diagnosis of High Speed Locomotive. *Mechanical Systems and Signal Processing*, **85**, 512-529. https://doi.org/10.1016/j.ymssp.2016.08.042

[20] Yi, C., Lv, Y. and Dang, Z. (2016) A Fault Diagnosis Scheme for Rolling Bearing Based on Particle Swarm Optimization in Variational Mode Decomposition. *Shock and Vibration*, **2016**, Article ID: 9372691. https://doi.org/10.1155/2016/9372691

[21] Lian, J., Liu, Z., Wang, H. and Dong, X. (2018) Adaptive Variational Mode Decomposition Method for Signal Processing Based on Mode Characteristic. *Mechanical Systems and Signal Processing*, **107**, 53-77. https://doi.org/10.1016/j.ymssp.2018.01.019

[22] Xiao, Q., Li, J. and Zeng, Z. (2018) A Denoising Scheme for DSPI Phase Based on Improved Variational Mode Decomposition. *Mechanical Systems and Signal Processing*, **110**, 28-41. https://doi.org/10.1016/j.ymssp.2018.01.019

[23] Cui, X., Huang, J., Li, C. and Zhao, Y. (2022) Three-Dimensional Instantaneous Orbit Map for Rotor-Bearing System Based on a Novel Multivariate Complex Variational Mode Decomposition Algorithm. *Mechanical Systems and Signal Processing*, **178**, Article ID: 109211. https://doi.org/10.1016/j.ymssp.2022.109211

[24] Rockafellar, R.T. (1973) A Dual Approach to Solving Nonlinear Programming Problems by Unconstrained Optimization. *Mathematical Programming*, **5**, 354-373. https://doi.org/10.1007/BF01580138

[25] Liu, Y., Chai, Y., Liu, B. and Wang, Y. (2021) Impulse Signal Detection for Bearing Fault Diagnosis via Residual-Variational Mode Decomposition. *Applied Science*, **11**, Article 3053. https://doi.org/10.3390/app11073053

[26] Zhang, G., Liu, H., Zhang, J., Yan, Y., Zhang, L., Wu, C., Hua, X. and Wang, Y. (2019) Wind Power Prediction Based on Variational Mode Decomposition. *Journal of Modern Power Systems and Clean Energy*, **7**, 281-288. https://doi.org/10.1007/s40565-018-0471-8

[27] Li, J., Yao, X., Wang, H. and Zhang, J. (2019) Periodic Impulses Extraction Based on

Improved Adaptive VMD and Sparse Code Shrinkage Denoising and Its Application in Rotating Machinery Fault Diagnosis. *Mechanical Systems and Signal Processing*, **126**, 568-589. https://doi.org/10.1016/j.ymssp.2019.02.056

[28] Li, H., Zhang, Y. and Zheng, H. (2010) Bearing Fault Detection and Diagnosis Based on Order Tracking and Teager-Huang Transform. *Journal of Mechanical Science and Technology*, **24**, 811-822. https://doi.org/10.1007/s12206-009-1211-9