Weak Fault Feature Enhancement of Acoustic Data Based on Variational Mode Decomposition

Gang Tang*, Chaoren Qin, Zhi Xu

College of Mechanical and Electrical Engineering
Beijing University of Chemical Technology
Beijing 100029, China
tanggang@mail.buct.edu.cn

Ying Chen

Chongqing Vehicle Test & Research Institute Co., Ltd.
Chongqing 401122, China

Abstract— **In the prognostic and health management of rotating machinery, the characteristic frequency of early weak fault is usually difficult to be extracted. To overcome this difficulty, this paper presents a weak fault feature enhancement method of acoustic data for rolling bearings based on variational mode decomposition (VMD). Firstly, the acoustic data is decomposed into some band-limited intrinsic mode functions (BLIMF) by the optimized VMD. Then an adaptive signal-to-noise ratio (ASNR) estimation method is proposed to determine the optimal BLIMF. Finally, the fault types of rolling bearings are identified through Hilbert envelope transform. Experimental results show that the presented method can effectively enhance the feature for early weak fault in rolling bearings with acoustic data.**

Keywords- variational mode decomposition; acoustic data; fault feature enhancement; adaptive signal-to-noise ratio

I. INTRODUCTION

Proper installation of sensors is the basis for equipment condition monitoring and fault diagnosis. However, since the contact sensors are not allowed to be installed to acquire the data in some special cases, such as nuclear power plant pipeline condition monitoring system. Therefore, we use acoustic sensor to get data. But, there are some disadvantages in acoustic data, such as low signal-to-noise ratio, which poses a greater challenge to the weak fault diagnosis of bearings [1].

There are plenty of useful solutions that are able to enhance the fault feature in rolling bearings [2-3], such as empirical mode decomposition (EMD). Due to these algorithms are essentially decomposed according to the recursive mode, they have the following drawbacks: (1) Sensitive to noise and sampling rate; (2) End effect; (3) Modal aliasing problems; (4) Lack of solid theoretical support. The VMD method is an adaptive signal processing method proposed by Dragomiretskiy et al. [3], which overcomes the above problems of EMD. It decomposes the signal by iteratively searching the center frequency and bandwidth of each mode by establishing overall framework of the variation [4]. In recent years, many scholars have studied VMD and achieved many results for rolling bearings based on vibration data [5-7]. In this paper, we present a weak fault feature enhancement method of acoustic data based on VMD. Firstly, we obtain the optimal VMD parameters through the envelope characteristic factor method. Then, the acoustic data is decomposed by VMD. Finally, the optimal mode is determined by the proposed ASNR method.

The main structure of this paper is as follows: In Section II, the basic theory of VMD and ASNR is introduced. The effect of the proposed method is verified by experiments in the Section III. We conclude this paper in Section IV.

II. THEORETICAL BACKGROUND

A. Variational Mode Decomposition

VMD is a widely accepted method of signal processing. It breaks down the signal into multiple BLIMFs by iterative solution. The following describes its principle [2].

It is assumed that the signal $x(t)$ can be decomposed into a certain number of intrinsic mode signals u_k having different center frequencies ω_k and limited bandwidth.

The unilateral spectrum of u_k is obtained by Hilbert transform, and the formula is as follows:

$$\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t) \tag{1}$$

where $\delta(\mathrm{t})$ is the Dirichlet function, j is an imaginary unit.

Then calculate the spectrum of each component on the baseband according to (2).

$$\left[\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t)\right]e^{j\omega_k t} \tag{2}$$

$$\min_{\{\mathrm{u_k}\},\{\omega_k\}}\left\{\sum\nolimits_{\mathrm{k}}\left\|\partial_{\mathrm{t}}\left[\left(\delta(\mathrm{t})+\frac{\mathrm{j}}{\pi\,\mathrm{t}}*u_{\mathrm{k}}(\mathrm{t})\right)\right]\mathrm{e}^{-\mathrm{j}\omega_{\mathrm{k}}\mathrm{t}}\right\|_2^2\right\}\mathrm{s.\ t.} \quad \sum_{\mathrm{k}}u_k=x \tag{3}$$

The variational constraint model formula of VMD is as (3).

In the above formula, $\{u_k\}=\{u_1,\cdots,u_K\}$ represents the K components of the decomposition, $\{\omega_k\}=\{\omega_1,\cdots,\omega_K\}$ represents the center frequency corresponding to every segment, $\sum_k$ is equivalent to $\sum_{k-1}^{K}$.

In order to obtain the optimal solution of the above constrained variational mode, the quadratic penalty factor α and the Lagrange multiplier λ of Lagrange function shown below is introduced in the VMD.

$$L(\{u_k\},\{\omega_k\},\lambda)=\alpha\sum_k\left\|\partial_t\left[\left(\delta(t)+\frac{j}{\pi t}*u_k(t)\right)\right]e^{-j\omega_k t}\right\|_2^2 + \left\|x(t)-\sum_k u_k(t)\right\|_2^2+\left\langle\lambda(t),x(t)-\sum_k u_k(t)\right\rangle \tag{4}$$

Update $\{u_k\},\{\omega_k\}$ by alternate iteration using alternative direction method of multipliers. Finally, the optimal solution is obtained.

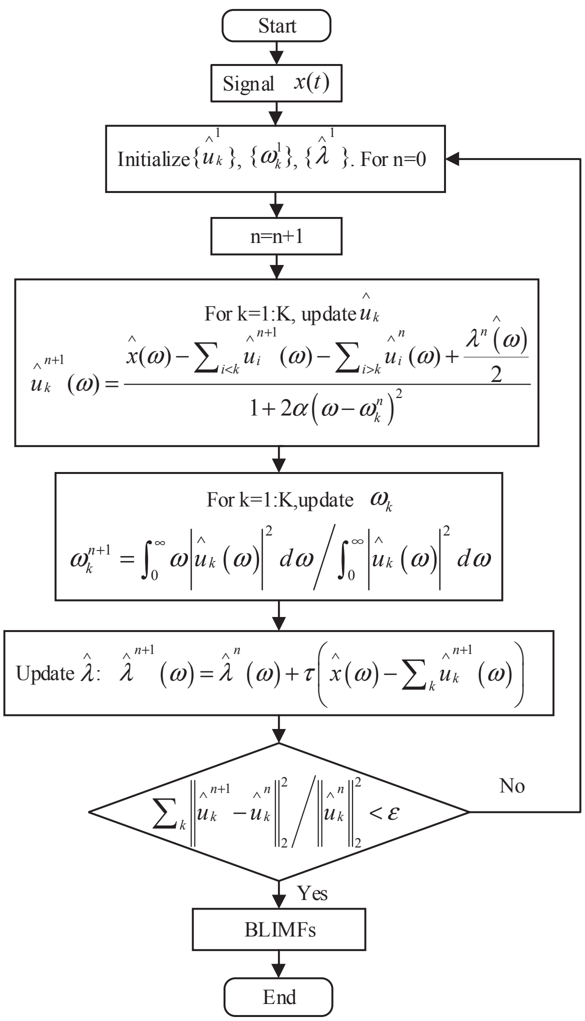

Figure 1. VMD algorithm flow

B. Adaptive Signal-to-noise Ratio

For a signal with known signal power and noise power, its signal-to-noise ratio can be calculated through (5). For the actual signal, scholars have proposed a number of methods to estimate the SNR. Here we introduce one of the most common ones [8]. Equation (6) introduces its calculation method.

$$SNR=10\log_{10}\left(\frac{P_{signal}}{P_{noise}}\right) \tag{5}$$

In the above formula, P_{signal} is the power of the signal, P_{noise} is the power of the noise, and the unit of the SNR is dB.

$$SNR=10\log 10\left(\frac{P\left[round\left(\frac{FCF}{\Delta f}\right)+1\right]}{\sum_{i=1}^{NFFT/2}P[i]-P\left[round\left(\frac{FCF}{\Delta f}\right)+1\right]}\right) \tag{6}$$

$P[i]$ is the power spectrum of the demodulation signal, Δf is the frequency resolution, NFFT is the length of FFT, FCF is fault characteristic frequency, round means round to nearest integer.

It is well known that VMD iteratively decomposes signals according to the principle of maximum energy. Therefore, there are many shortcomings in using (6) to calculate the SNR of BLIMF. For example, if the noise frequency with high energy appears near the fault frequency, the above SNR calculation method cannot correctly estimate the SNR of the signal. So, to overcome these difficulties, this paper proposes an adaptive SNR (ASNR) estimation method. ASNR is calculated by (8).

$$Ku=\frac{E[x-\mu]^4}{\sigma^4}=\frac{1}{N}\sum_{i=1}^{N}\left[\frac{x_i-\mu}{\sigma}\right]^4 \tag{7}$$

$$ASNR= 10\log 10\left(\frac{P\left[round\left(\frac{FCF}{\Delta f}\right)+1\right]\sum_{i=1}^{N}\left[\frac{x_i-\mu}{\sigma}\right]^4}{N\left\{\sum_{i=1}^{NFFT/2}P[i]-P\left[round\left(\frac{FCF}{\Delta f}\right)+1\right]\right\}}\right) \tag{8}$$

Where μ is the mean of the signal, σ is the variance of the signal. The kurtosis coefficient is a dimensionless parameter. Since it is independent of the bearing's speed, size and load, and it is particularly sensitive to shock signals, so it is suitable for surface damage diagnosis, especially early weak fault diagnosis. Therefore, combining SNR with kurtosis, the ASNR can well solve the SNR problems mentioned above.

III. EXPERIMENTAL VERIFICATION

This section will prove the effectiveness of the proposed method through experiments. The rolling bearing fault simulation test rig is shown in Fig. 2.

The test bench is driven by the electric motor, and the power is transmitted to the rotating shaft through the coupling.

The position of the faulty bearing and the microphone sensor are also shown in the Fig. 2.

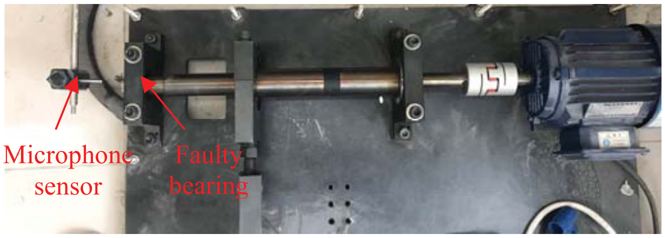

Figure 2. Rolling bearing fault simulation test rig.

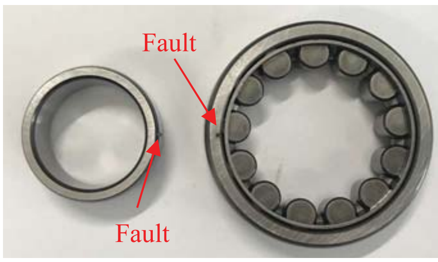

Figure 3. Faulty Bearing.

The model of faulty bearing is NSK NU205EW. As shown in Fig 3, the wire cutting process is used to process the fault in the inner and outer rings. The frequency of the shaft rotation speed measured by the photoelectric sensor is 21.82 Hz, which is 1309.2 r/min. Through the above data, we can query the fault frequency through the NSK official website. The specific information is shown in TABLE I. The sampling frequency of the signal is set to 20000 Hz. We select 40,000 points of the collected acoustic data for analysis.

TABLE I. BEARING FAULT CHARACTERISTIC FREQUENCY

Rotation frequency (f)	21.820 Hz
Inner ring defect frequency (f_i)	169.105 Hz
Outer ring defect frequency (f_o)	114.555 Hz
Rolling element defect frequency (f_r)	109.268 Hz

First we plot the waveform and Hilbert envelope spectrum (Fig. 4) of the original data. From the waveform, we can find that the amplitude is low, the vibration shock is not obvious, and the noise is large. In the corresponding envelope spectrum, only the second harmonics of the rotation frequency can be found, and all the fault frequencies are completely masked by noise.

Then, some preprocessing is performed on the signal, and the optimal K=6, a=2000 is selected by the envelope feature factor method. Next, the signal is processed by VMD. Finally, calculate the SNR, Ku and ASNR values of each BLIMF, and the calculation results are listed in the TABLE II.

The kurtosis value of BLIMF6 is significantly larger than others, which indicates that BLIMF6 contains relatively large fault impulsive character. From TABLE II we can see that the SNR values of BLIMF5 and BLIMF6 are similar, so it is hard to determine which one is the optimal BLIMF with the SNR value. Nonetheless, through the ASNR method, it can clearly determined that BLIMF6 is the optimal mode. To verify the correctness of the method, we plot waveform and envelope spectrum of each BLIMF.

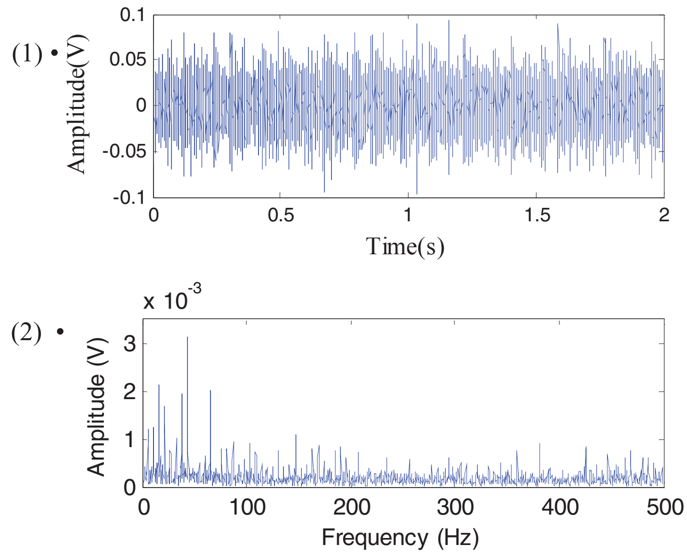

Figure 4. (1) Waveform of original acoustic data. (2) Hilbert envelope spectrum of original acoustic data

TABLE II. THE VALUE OF KU, SNR AND ASNR

BLIMF	**Ku**	**SNR (dB)**	**ASNR(dB)**
1	3.57	-31.32	-19.71
2	4.41	-22.26	-11.13
3	3.61	-24.44	.14.81
4	3.64	-22.12	-11.15
5	3.66	-17.28	-7.88
6	6.65	-17.02	-4.70

Fault frequency is not clear on the envelope spectrum from BLIMF1 to BLIMF4, but the overall trend corresponds to the ASNR and SNR values, which also verify the correctness of the method.

From envelope spectrum of BLIMF5, it can clear see the fundamental frequency of the two fault frequency. Although the second harmonics of the inner ring fault frequency can be found, the amplitude is lower. The second harmonics of the outer ring fault is hard to find. Only the appearance of the fundamental frequency does not fully prove that the bearing has failed. However, it can clearly find the second harmonics of the rotation frequency and the fundamental frequency and its second harmonics of the inner outer ring fault in the envelope spectrum of BLIMF6. From the waveform of BLIMF6 can also see obvious cyclical impulse. Under normal circumstances, when the fundamental frequency and frequency multiplication of the fault frequency appear obviously at the same time, as well as the occurrence of periodic shock on the waveform, the bearing fault can be judged.

Compared with BLIMF5 and BLIMF6, BLIMF6 can be determined as the optimal component. Through the above experimental results, the effect of the proposed method is well proved.

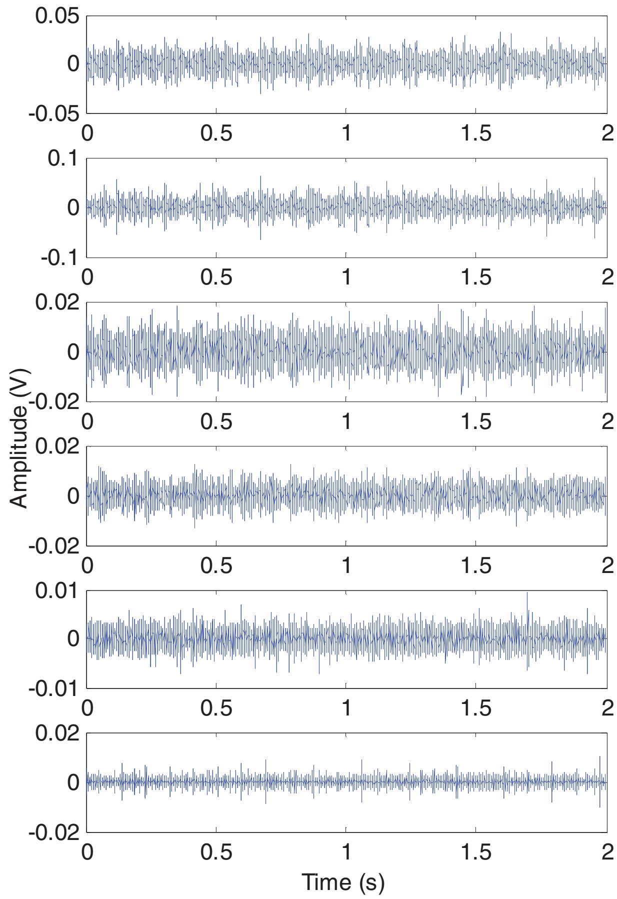

Figure 5. Waveform of BLIMF1-BLIMF6 from top to bottom

IV. Conclusions

In this paper, a fault feature enhancement strategy for early weak fault of rolling bearings with acoustic signals based on VMD and ASNR is proposed.

(1) VMD has a good application in dealing with the vibration data of rolling bearing. This paper applies it to process acoustic data, and gets ideal results. It provides an approach to solve the problem that the SNR of acoustic signals is low and the early weak fault feature is difficult to extract.

(2) On the basis of the optimal mode, we can carry out the next step, such as blind source separation.

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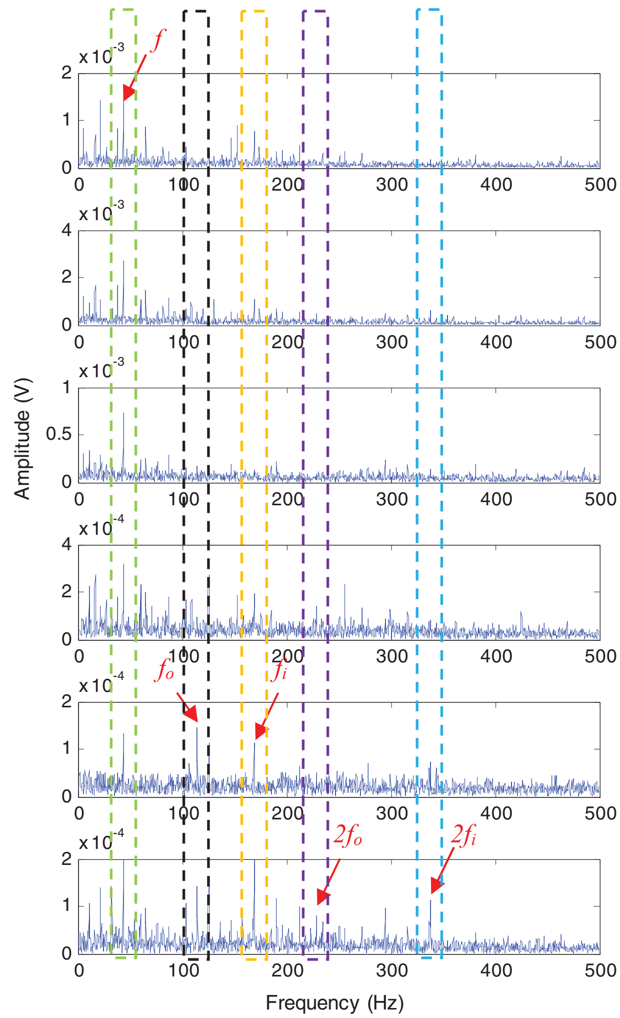

Figure 6. Envelope spectrum of every BLIMF in order

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