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Applications of the Minimum Entropy Deconvolution for the Feature Enhancement of Rolling Bearings

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Abstract: In order to enhance the impulsivity of the vibration, which is induced by the incipient fault of rolling element bearings, the Minimum Entropy De-convolution (MED) method is introduced in this paper. By formulating an inverse filter, the MED method is used to counteract the effect of the signal transmission path so as to recover the input impulses. The impulsivity of the fault vibration signal can be enhanced by MED. The simulated and experimental vibration signals are used to validate the efficacy of the proposed method. It is shown that no matter the inner race fault or outer race fault induced vibration, the corresponding kurtosis is apparently increased when the signal is filtered by the designed optimal inverse filter. The experimental vibration comes from the bearing center of Case Western Reserve University. It is indicated that the MED method could efficiently enhance the feature of the fault induced vibration and is valuable in the engineering application.

Keywords: Minimum entropy de-convolution; Feature enhancement; Weak fault; Rolling element bearings

1. Introduction

As one of the most common used components in the engineering, the rolling element bearings are closely related to the performance of the machines. For example, many faults and incidents are caused by bearing failures. Therefore, the condition monitoring and fault diagnosis of rolling element bearing is of great significance for the safety running of the machines, and many fault diagnostic methods, such as, impulse detection method, impulse energy detection, oil analysis, and vibration analysis, were proposed to diagnose the bearing fault. Thereinto, the vibration analysis method is the most widely used owing to the non-invasive nature and high sensitive to the incipient faults. [1-5]

Generally, the impulses can be produced and will enforce the natural response of the bearing system when faults occur [6]. Therefore, the accurate extraction of these impulse responses is the key point of the bearing fault diagnosis. The spectral kurtosis is an efficient index for the determine of the carrier frequency of the impulse responses [7-10]. However, when the rotating speed is very high, the fault characteristic frequency is close to the carrier frequency and the spectral kurtosis cannot exactly estimate the carrier frequency. In 2007, Endo and Randall introduced a new fault feature enhancement method, named minimum entropy deconvolution (MED), to diagnose the gear faults and validate the efficacy of its application on the gear fault diagnosis [11]。

In this paper, in order to extract the weak signal produced by the incipint bearing fault, the MED method is introduced to enhance the fault feature of the bearing fault. Simulations and experiments are used to validate the efficacy.

2. Minimum Entropy Deconvolution

Minimum Entropy Deconvolution, proposed by Wiggin in 1987, was firstly used to extract the reflected signal of the earthquake data. Using an inverse filter to eliminate the influence of the transform path, the MED can recover the input signal from the collected signals. The detailed sketch of the MED is illustrated in Fig. 1, in which d(t) denotes the input of the system, h(t) denotes the unit impulse response function, n1(t) denotes the input noise, n2(t) denotes the noise of the output end, y(t) denotes the output response of the system, v(t) denotes an inverse filter of MED and x(t) denotes the estimation value of the input signal obtained by v(t). The corresponding equation of the MED is given by

$$y(t) = \left\{ d(t) + n_1(t) \right\} * h(t) + n_2(t) \qquad (1)$$

where * denotes the convolution operator.

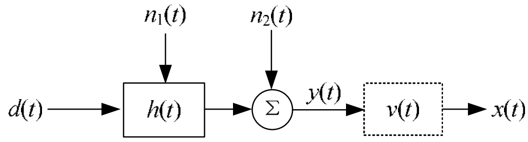

Figure 1. Sketch of the MED

Since the MED is mainly used to eliminate the influence of the transform path, therefore, the noise of the input end is usually neglected in applications and Eq. (1) can be rewritten as

$$y(t) = d(t) * h(t) + n_2(t) \quad (2)$$

and the corresponding discrete form is given by

$$y(n) = \sum_{m=1}^{M} h(m) d(n-m) + n_2(n), \quad n = 1, 2, \cdots, N \quad (3)$$

where M denotes the length of the unit impulse response function and N denotes the length of the collected signal. Generally, $N \gg M$. As Eq. (3) shows, the system is equivalent to a filter h(t). Therefore, the MED method will design a suitable inverse filter used to eliminate the filter effect of the system and obtain the estimation of the input signal——x(t)。

$$x(t) = y(t) * v(t) \quad (4)$$

The corresponding discrete form is

$$x(n) = \sum_{l=1}^{L} v(l) y(n-l) \quad (5)$$

In general, the estimation signal x(t) cannot exactly equal the original input signal d(t), however, the more efficient of the inverse filter, the more closer of the estimation to the original signal.

Suppose that the system is a linear in-variant causal system and the input signal is impulsive, then

$$K(v(l)) = \frac{\sum_{n=1}^{N} x^4(n)}{\left[\sum_{n=1}^{N} x^2(n)\right]^2}, \quad l = 1, 2, \cdots, L \quad (6)$$

Where L denotes the length of v(t). The optimal inverse filter is the filter coefficient of Eq. (6), when Eq. (6) gets the maximum value. Namely,

$$\frac{\partial K(v(l))}{\partial v(l)} = 0 \quad (7)$$

Therefore, the following equations exist

$$\frac{\partial K(v(l))}{\partial v(l)} = \frac{\left(\sum_{n=1}^{N} x^2(n)\right)^2 4\sum_{n=1}^{N} x^3(n)\frac{\partial x(n)}{\partial v(l)} - 4\left(\sum_{n=1}^{N} x^4(n)\right)\left(\sum_{n=1}^{N} x^2(n)\right)\left(\sum_{n=1}^{N} x(n)\frac{\partial x(n)}{\partial v(l)}\right)}{\left(\sum_{n=1}^{N} x^2(n)\right)^4} \quad (8)$$

Combineing Eq.（7）, then we can get

$$\left(\sum_{n=1}^{N} x^3(n)\frac{\partial x(n)}{\partial v(l)}\right)\left(\sum_{n=1}^{N} x^2(n)\right)^2 - \left(\sum_{n=1}^{N} x^4(n)\right)\left(\sum_{n=1}^{N} x^2(n)\right)\left(\sum_{n=1}^{N} x(n)\frac{\partial x(n)}{\partial v(l)}\right) = 0 \quad (9)$$

Namely

$$\frac{\sum_{n=1}^{N} x^2(n)}{\sum_{n=1}^{N} x^4(n)}\left(\sum_{n=1}^{N} x^3(n)\frac{\partial x(n)}{\partial v(l)}\right) = \sum_{n=1}^{N} x(n)\frac{\partial x(n)}{\partial v(l)} \quad (10)$$

Based on Eq.（5）, the following equation exists

$$\frac{\partial x(n)}{\partial v(l)} = y(n-l) \quad (11)$$

Substituting Eq.（11）into Eq. (10), then

$$\frac{\sum_{n=1}^{N} x^2(n)}{\sum_{n=1}^{N} x^4(n)}\left(\sum_{n=1}^{N} x^3(n) y(n-l)\right) = \sum_{n=1}^{N} x(n) y(n-l) = \sum_{m=1}^{L} v(m) \sum_{n=1}^{N} y(n-m) y(n-l) \quad (12)$$

Let $b = \frac{\sum_{n=1}^{N} x^2(n)}{\sum_{n=1}^{N} x^4(n)}\left(\sum_{n=1}^{N} x^3(n) y(n-l)\right)$, $A = \sum_{n=1}^{N} y(n-m) y(n-l)$, $u = \sum_{m=1}^{L} v(m)$, then Eq. (12) can be rewritten as the matrix form

$$b = Au \quad (13)$$

Therefore, the coefficient of the inverse filter is given by

$$u = A^{-1} b \quad (14)$$

In applications, the optimal coefficient of the inverse filter given by Eq. (14) is obtained iteratively and corresponding procedure is listed as the following.

Setting the length of the inverse filter v(t) as L, then calculate the auto correlation matrix A, with the dimension of $L \times L$.

Initial the coefficient of the filter u: $u^{(0)} = 1$.

Calculate the output signal of the inverse filter, namely

$$x(n) = \sum_{l=1}^{L} u^{(i-1)}(l) y^{i}(n-l), \quad i = 1, 2, \cdots, I \quad (15)$$

where i denotes the amount of the iteration.

Calculate the vector b,

$$b^{(i)} = \frac{\sum_{n=1}^{N} x^2(n)}{\sum_{n=1}^{N} x^4(n)}\left(\sum_{n=1}^{N} x^3(n) y(n-l)\right) \quad (16)$$

On the basis of Eq. (14), calculate the inverse filter coefficient $u^{(i)} = A^{-1} b^{(i)}$

Calculate the convergence coefficient

$$E = \frac{\| u^{(i)} - u^{(i-1)} \|}{\| u^{(i-1)} \|} \quad (17)$$

If $E < E_T$, a prior set convergence threshold or the iteration extends the maximum amount of the set value I, then terminate the iteration and output the result. Otherwise, return to step (3) and continue the iteration procedure.

3. Simulations

In this section, simulations are used to validate the efficacy of the MED method. For the sake of simplification, the bearing system is treated as a single degree of freedom system, and the impulse responses produced by the bearing fault is given by

$$x(t) = A(t)\sum_{k=-\infty}^{\infty} e^{-2\pi\xi f_n (t-k\Delta T)} \sin\left(2\pi f_n (t-k\Delta T)-\phi_0\right) \quad (18)$$

where A(t) denotes the amplitude of the impulse response, denotes the relative damping ratio, fn denotes the resonant frequency, 0 denotes the initial phase angle and T denotes the interval of the adjacent impulse responses。 In applications, since about 90% of the bearing failure is caused by the inner or outer race fault, therefore, only inner and outer race faults are involved here.

3.1. Outer Race Fault Simulation

Let A(t)=1, =0.03, fn=3 kHz, T=0.01 s, the outer race fault signal can be produced by Eq.(18) and illustrated in Fig. 2a. Added with the white noise of -5 dB, the outer race fault signal is sampled at the frequency of 15 kHz and lasts 2 s. It can be seen that the impulsive character is not very visible in the collected signal owing to the contamination of the noise. Let the length of the MED inverse L=100, the maximum iteration I=30 and the convergence threshold ET=0.01, the signal is processed by the proposed MED inverse filter and the filtered signal is illustrated in Fig. 1b. It can be seen that the impulsive character of the signal apparently increases. The coefficient of the designed inverse filter is shown in Fig.2 and the kurtosis of the signal obtained by the iteration calculation is shown in Fig.3. It can be seen that the kurtosis of the estimation input signal increases with the iteration of the procedure. It can be concluded that the MED method can efficiently increase the impulse character of the outer race fault signal.

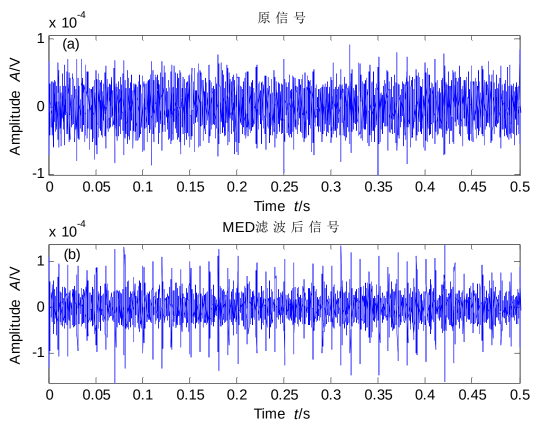

Figure 1. The outer race fault simulation (a) original simulation signal; (b) the signal filtered by the MED method

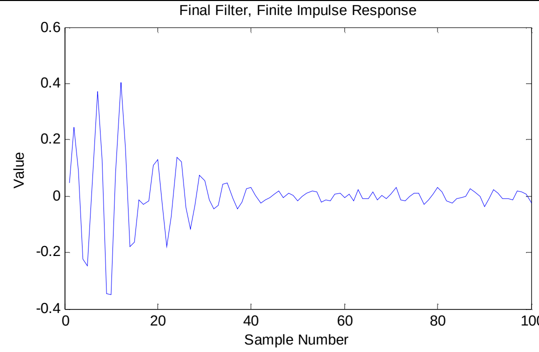

Figure 2. The coefficient of the inverse filter applied on the outer race fault signal

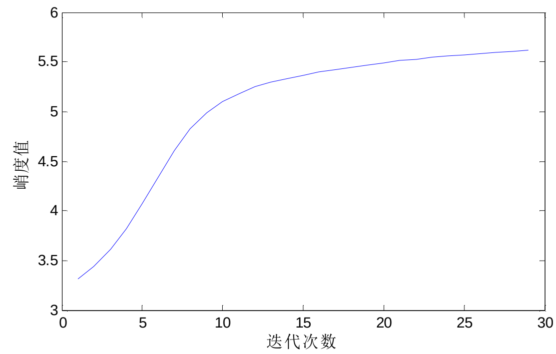

Figure 3. The kurtosis of the signal obtained by the iteration of the MED

3.2. Inner Race Fault Simulation

Let $A(t)$ $\cos(2\pi\times 22.2t)+1.5$, =0.03, fn=3 kHz, T=0.01 s, the inner race fault simulated signal can be produced by Eq.(18) and illustrated in Fig. 4a. Added with the white noise of -5 dB, the simulated signal is sampled at the frequency of 15 kHz and lasts 2 s. It can be seen that the impulse responses of the inner race fault signal is not obvious owing to the contamination of the noise. Let the length of the inverse MED filter L=100, the maximum iteration I=30 and the convergence threshold ET=0.01, the signal is obtained by the MED filter and illustrated in Fig. 4b. Apparently, the impulses character is increased by the MED filter. Fig.5 illustrates the corresponding the coefficient of the inverse MED filter and Fig. 6 illustrates the kurtosis of the iteration signal obtained by the MED method. It can be seen that the impulse character of the inner race fault signal can be efficiently increased by the MED method.

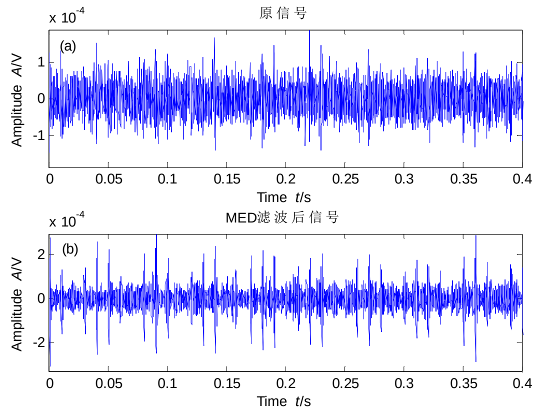

Figure 4. The inner race fault simulated signal (a) the original simulated signal; (b) the filtered signal obtained by the MED method

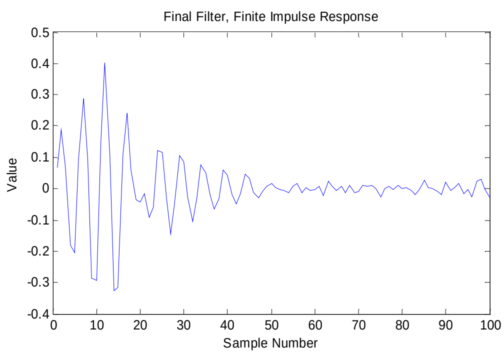

Figure 5. The coefficient of the MED filter applied on the inner race fault signal

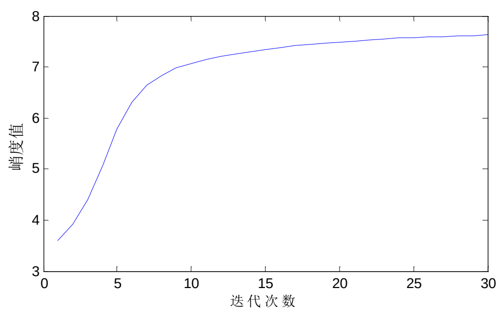

Figure 6. The kurtosis of the iteration signal obtained by the MED method

4. Case Studies

In this section, the experimental data collected in the bearing data center of Case Western Reserve University (CWRU) are used to validate the efficacy of the MED method. The test stand of the experiment is illustrated in Fig. 7. The electric motor with 2 horse power was located at the left end, while a power consumer is located at the right end. The test bearing is installed at the test end of the motor. An inner race fault of 0.007 inch and an outer race fault of 0.014 inch were introduced by an electric machining respectively. An accelerator is located at the bearing house with a magnetic base. The bearing type is 6205-2RS JEM SKF. The collected vibration is sampled at the frequency of 2 kHz at the rotating speed of 1796 r/min.

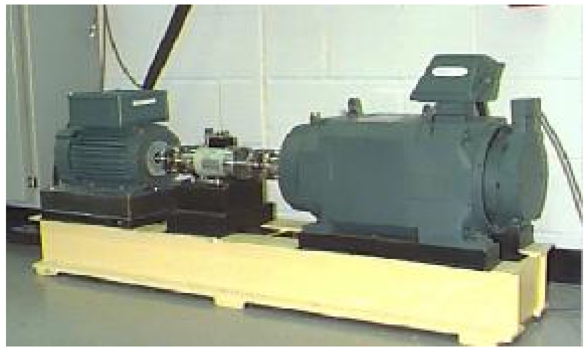

Figure 7. The bearing test stand of CWRU

4.1. Case 1: Outer Race Fault

Fig. 8 illustrates the temporal waveform of the outer race fault signal and corresponding signal obtained by the MED inverse filter, whose parameters were set as the following: the length of the inverse filter L=100, the maximum iteration I=30 and the convergence threshold ET=0.01. Figs.9 and 10 are the coefficient of the inverse filter and the kurtosis of the iterative estimation input signal obtained by the MED method. It can be seen that the impulse character of the signal increases apparently owing to the increment of the kurtosis, which indicates that the MED method can enhance the impulse character of the outer race fault signal.

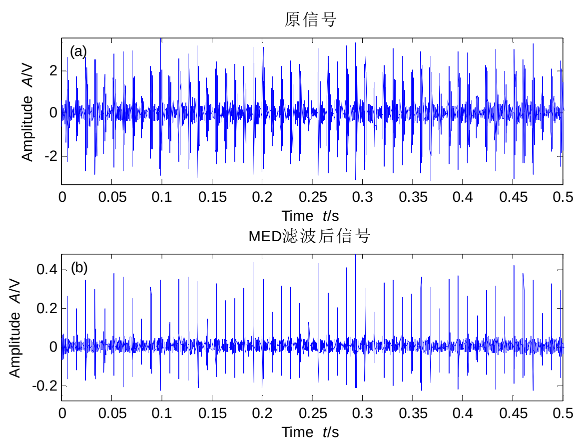

Figure 8. The outer race fault signal of CWRU (a) the original waveform (b) estimation input signal obtained by the MED inverse filter

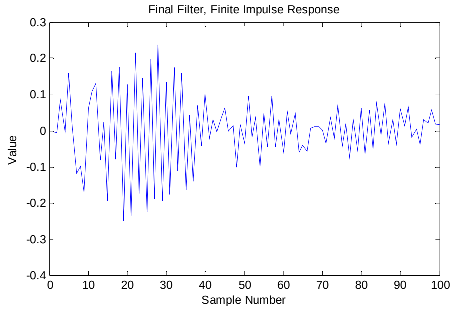

Figure 9. Coefficients of the MED inverse filter of the outer race fault signal

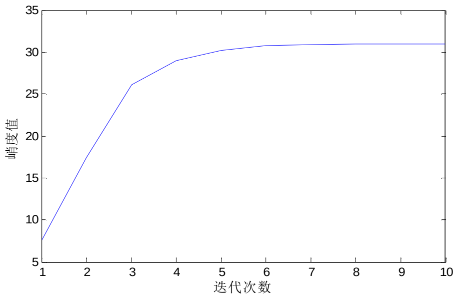

Figure 10. Kurtosis of the estimation input signal obtained by the iteration operation

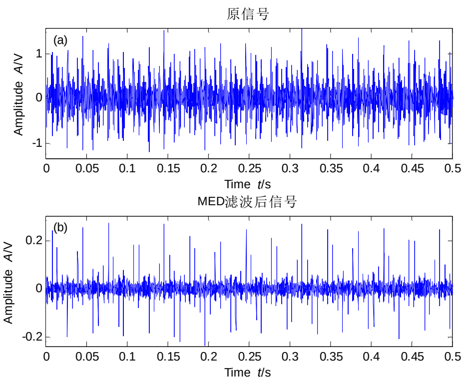

Figure 11. The inner race fault signal of CWRU (a) the original waveform (b) the estimation input signal obtained by the MED inverse filter

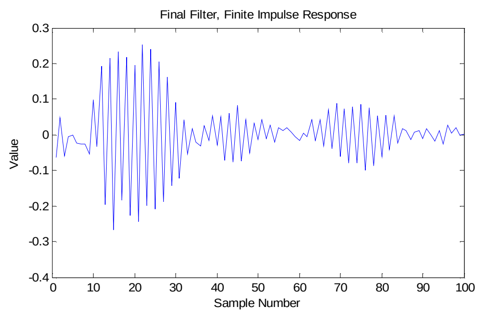

Figure 12. Coefficients of the MED inverse filter applied on the inner race fault signal

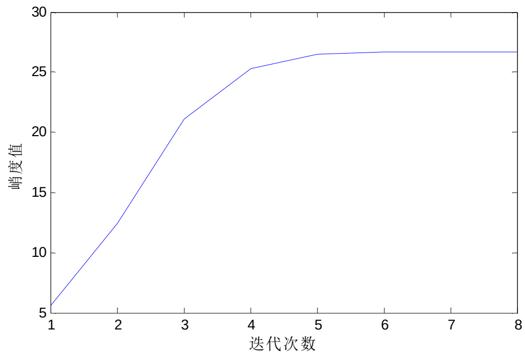

Figure 13. Kurtosis of the estimation input signal obtained by the iteration of MED method

4.2. Case 2: Inner Race Fault

Fig.11 illustrates the temporal waveform of the inner race fault signal and corresponding signal obtained by the MED inverse filter, whose parameters were set as the following: the length of the inverse filter L=100, the maximum iteration I=30 and the convergence threshold ET=0.01. Figs.12 and 13 are the coefficient of the inverse filter and the kurtosis of the iterative estimation input signal obtained by the MED method. It can be seen that the impulse character of the signal increases apparently owing to the increment of the kurtosis, which indicates that the MED method can enhance the impulse character of the inner race fault signal.

Conclusions

To solve the problem that the weak fault signal of rolling bearings are easily smeared by the noise, the MED method was applied to the feature enhancement of the rolling bearings. By designing an optimal inverse filter to eliminate the influence of the transform path, the MED inverse filter can obtain an estimation input of the fault signal and enhance the impulse character of the signal. Moreover, both simulations and experiments were used to validate the efficacy of the proposed MED method. It is shown that the MED method can efficiently enhance the impulse character of the inner and outer race fault signal and is greatly helpful for the feature extraction of the bearing fault character.

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