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A joint adaptive wavelet filter and morphological signal processing method for weak mechanical impulse extraction †

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Abstract

Periodical impulses are vital indicators of rotating machinery faults. Therefore, the extraction of weak periodical impulses from vibration signals is of great importance for incipient fault detection. However, measured signals are often severely tainted by various noises, which makes the detection of impulses rather difficult. As such, a proper signal processing technique is necessary. In this paper, a hybrid method comprised of wavelet filter and morphological signal processing (MSP) is proposed for this task. The wavelet filter is used to eliminate the noise and enhance the impulsive features. Then, the filtered signal is processed by the morphological closing operator and a local maximum algorithm to isolate periodical impulses. To select the proper parameters of the joint approach, i.e., the center frequency, the bandwidth of wavelet filter, and the length of flat structuring elements (SE), a novel optimization algorithm based on differential evolution (DE) is developed. The results of simulated experiments and bearing vibration signal analysis verify the effectiveness of the proposed method.

Keywords: Morphological signal processing; Wavelet filter; Differential evolution; Impulse extraction; Fault diagnostics

1. Introduction

The early fault detection of machinery elements, such as gears and roller bearings, is crucial for avoiding catastrophic failures and saving production loss costs. Various techniques have been developed for this task. One of the major approaches is based on the analysis of vibration signals measured through the accelerometers mounted on or near the critical mechanical components. Vibration signals contain rich information, where the periodical impulses—the indicators of machinery faults—are most attractive [1-4]. However, such impulses are very weak in the early stage of defects, and often overwhelmed by strong noise. Therefore, an effective signal processing method is necessary for the extraction of impulses generated by fault.

Recently, a new method named morphological signal processing (MSP) has been introduced into the fault diagnosis of rotating machinery [5-10]. MSP is a nonlinear time-domain processing algorithm with four basic operators: erosion, dilation, opening and closing [11-13]. The fundamental concept of MSP is to modify the shape of signals through its interaction with another object, called the structuring element (SE). Nikolaou and Antoniadis [5] used the closing operator with a flat SE to extract envelopes of bearing vibration signals, and through a simulation study, they recommended that an SE with the length of 0.6-0.7 times the impulse repetition period (IRP) could minimize noise effects. Zhang et al. [8] also used the closing operator with a flat SE, which is 0.6~0.8 times the IRP in length, to extract impulsive features from gear vibration signals. Patargias et al. [7] proposed a morphological index (MI) that is the root mean square (RMS) value of the impulses isolated by the closing operator for rolling bearings monitoring.

Since MSP has many advantages, such as ease of use, good sensitivity to the local geometric characteristics of signals, high efficiency and effectiveness in processing impulsive signals, we also adopt it as a prototype to develop an effective method for the extraction of weak periodical impulses under heavily noisy circumstance. However, there exist two deficiencies of MSP that should not be overlooked. First, if the noise strength is so high that fault-generated impulses are fully embedded by noise, then the performance of MSP would deteriorate, for it mainly depends on the shape of signals. Second, its implementation requires the prior knowledge of signals to define the length of flat SE, thus lacking self-adaptation. To solve the first problem, we propose to apply the Morlet wavelet filter, which is a powerful method for signal de-noising [2, 14-17], prior to MSP. After wavelet filtering, certain noises

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and interferences can be removed, and the capability of MSP in impulse extraction can be improved. As for the second problem, we design an adaptive optimization scheme based on different evolution (DE) [18-22] to construct the optimal flat SE and Morlet wavelet filter simultaneously. By combining the optimal wavelet filtering and MSP, an effective tool for weak impulse extraction is developed, and it has great potential in the incipient fault detection of machinery elements.

The rest of this paper is organized as follows: Section 2 introduces the basic theories of MSP and compares two different MSP-based diagnostic approaches. Section 3 presents the principles of the Morlet wavelet filter. Section 4 proposes a novel scheme for the construction of the optimal Morlet wavelet filter and flat SE. In section 5, the proposed joint method is evaluated using simulation signals, and compared to a wavelet thresholding approach based on maximum likelihood estimation (MLE). In section 6, the proposed method is applied to bearing fault detection and identification. Finally, conclusions are drawn in section 7.

2. Discussion on morphological signal processing

MSP is a nonlinear approach developed from set theory and integral geometry and has been widely used in the areas of image processing and pattern recognition. Unlike traditional signal processing methods, such as the Fourier transform and wavelet transform, MSP deals with a signal waveform in the complete time domain rather than in the frequency domain. The basic operators of MSP include dilation, erosion, opening and closing [13]. Let $f(n)$ be the original discrete signal over a domain $F = (0,1,2, \cdots,N\text{-}1)$, and $g(n)$ be the SE, which is a discrete function over a domain $D_g = (0, 1, 2, \cdots, M\text{-}1)$. The four basic morphological operators are defined as follows:

Dilation:

$$\mathrm{dil}(n) = (f \oplus g)(n) = \max_{m \in D_g} [f(n-m) + g(m)] \tag{1}$$

Erosion:

$$\mathrm{er}(n) = (f \ominus g)(n) = \min_{m \in D_g} [f(n+m) - g(m)] \tag{2}$$

Opening:

$$\mathrm{op}(n) = (f \circ g)(n) = (f \ominus g \oplus g)(n) \tag{3}$$

Closing:

$$\mathrm{cl}(n) = (f \bullet g)(n) = (f \oplus g \ominus g)(n) \tag{4}$$

There are various kinds of SEs, such as flat SE, triangular SE, semicircular SE, etc. In this paper, the flat SE is used because it is the simplest one among SEs and appears to be quite appropriate for detecting impulses [7]. A flat SE is defined as a zero series with a length of M, i.e. $g=\{0,0,\cdots,0\}_{1\times M}$. It has only one parameter to be selected before application, namely its corresponding length M.

The closing operator is often employed by researchers to extract morphological envelopes of vibration signals. After that, there are mainly two approaches for further treatment. The first is to calculate the power spectrum of morphological envelopes to extract the impulse repetition frequency (IRF) [5]. The second is to isolate local peaks of morphological envelopes [7]. The latter method seems to be more effective than the former, because when a signal is heavily clouded by noise, its morphological envelope would mainly consist of the profile of noise. As a result, it would be hard to extract the IRF from the power spectrum. On the contrary, by experimental observation, the original impulses generally present as low energy sharply peak on the morphological envelope after MSP. Therefore, useful information can be obtained by isolating these peaks. To illustrate this point, a simulated study is conducted.

The simulated signal is a typical series of exponentially decaying impulses with the impulse function of $f(t)=e^{-4000t}$ sin (2π6000t) and the IRF of 40 Hz. The sampling frequency is 20 kHz. A significant amount of Gaussian noise is added to the original impulsive signal, and the resulting noisy signal is shown in Fig. 1(b) (SNR= -11 dB). The two approaches are compared using the noisy signal. The morphological envelope and its power spectrum are given in Fig. 2(a) and (b), respectively. We can see the IRF of 40 Hz is not evident in the power spectrum. Fig. 3 gives the local peaks isolated from the morphological envelope. It is easy to find that the extracted peaks are periodical with a period of approximate 40 Hz, corresponding to the original IRF. Therefore, in real applications, it is more practicable to isolate the local peaks of a morphological envelope than to calculate its power spectrum. This impulse extraction scheme based on the morphological clos-

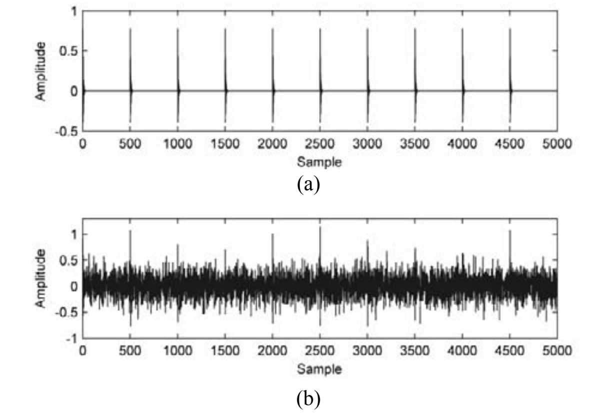


Fig. 1. (a) The simulated impulsive signal; (b) the simulated impulsive signal with Gaussian noise added (SNR = -11 dB).

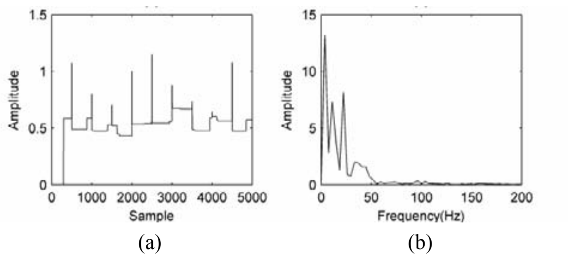


Fig. 2. (a) The morphological envelope obtained by the closing operator; (b) the power spectrum of the envelope.

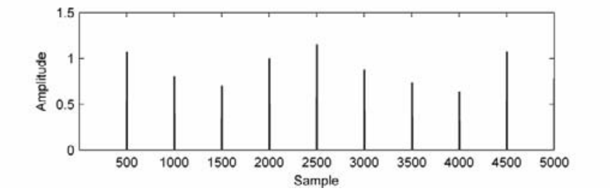
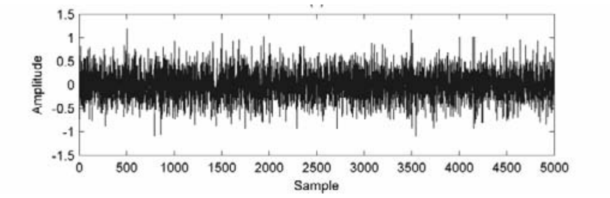
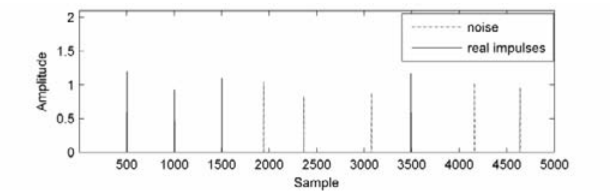


Fig. 3. The impulses extracted by the MIE method.



(a)



(b)

Fig. 4. (a) The simulated impulsive signal added with heavy noise (SNR = -16 dB); (b) the extracted impulses using the MIE method.

ing operator and local peak isolation is called the morphological impulse extraction method (MIE) in this study.

In the MIE method, local peaks are isolated by a simple local maximum algorithm:

$$p(i) = \begin{cases} cl(i), & \text{if } cl(i-1) < cl(i) \wedge cl(i) > cl(i+1) \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

where $cl(i)$ is the morphological envelope obtained by the closing operator [Eq. (4)].

To further assess the performance of the MIE method, we add more Gaussian noise to the original impulsive signal shown in Fig. 1(a). The resulting noisy signal with an SNR of -16 dB is shown in Fig. 4(a). The outcome of the MIE is given in Fig. 4(b), from which we can see that only a portion of the original impulses are isolated and several high amplitude noises are falsely extracted as impulses. This means the performance of the MIE method deteriorates because of the extremely heavy noise. To make the extraction of impulses more effective, robust and accurate, a straightforward way is to apply a de-noising method before the MIE to trim down noise. In this paper, wavelet filtering is chosen for this purpose. By combining the Morlet wavelet filter and MIE, an effective tool for early fault detection of machinery elements is developed.

3. Morlet wavelet filter

As discussed in the previous section, the performance of the MIE method would be affected by strong noise. To address this problem, we propose to apply the Morlet wavelet filter prior to MIE to trim down the noise in this study. The Morlet wavelet filter is a popular method used in machinery fault diagnosis and possesses excellent de-noising ability, as validated in many studies [14-17]. The basic idea of the wavelet filtering is to process a signal using wavelet transform at a fixed scale. Its basic principles are illustrated below.

The continuous wavelet transform (CWT) of $x(t)$ with respect to a mother wavelet $\psi(t)$ is defined as follows [23]:

$$WT(a,\tau) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t) \psi^* \left(\frac{t-\tau}{a} \right) dt \tag{6}$$

where

$$\psi_{(a,\tau)}(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-\tau}{a}\right) \tag{7}$$

a and τ are the scaling parameter and time localization parameter, respectively.

By applying the Fourier Parseval formula, Eq. (6) can be rewritten as frequency integration:

$$WT(a,\tau) = F^{-1}\{X(f)\sqrt{a}\Psi^*(af)\} \tag{8}$$

where $X(f)$ and $\Psi(f)$ are the Fourier transforms of $x(t)$ and $\psi(t)$, respectively, and F^{1} denotes the inverse Fourier transform.

According to Eq. (8), the wavelet transform $WT(a,\tau)$ for a fixed scale can be interpreted as a filtering process using a filter with an impulse response equal to $\sqrt{a}\Psi(af)$. In other words, the convolution process in the wavelet transform is simply a filtering operation if the daughter wavelet is treated as a filter kernel. The frequency response of the wavelet filter varies as the shape and scale of the wavelet change. Therefore, low-pass, high-pass, band-pass or even multiple-band pass filters can be built by the wavelet transform at selected scales.

The choice of wavelet basis is very crucial for the application of wavelet transform. By a series of tests and comparisons, it is found that the Morlet wavelet, which has a similar shape to an impulse, gives superior results to other wavelet bases [4, 24]. Therefore, we adopt the Morlet wavelet to construct "match filter" for impulsive signals.

The Morlet wavelet is defined in the time domain as a sinusoidal wave multiplied by a Gaussian function:

$$\psi(t) = \frac{\sigma}{\sqrt{\pi}} e^{-\sigma^2 t^2} e^{i2\pi f_0 t} \tag{9}$$

where σ is the shape factor and f_0 is the wavelet center frequency.

The Fourier spectrum of the Morlet wavelet is given by:

$$\Psi(f) = e^{-(\pi^2/\sigma^2)(f-f_0)^2} \tag{10}$$

By Eq. (10), it can be easily obtained that the half-bandwidth of the Morlet wavelet is:

$$\beta = \frac{\sqrt{2\ln 2}}{\pi}\sigma \quad (Hz) \tag{11}$$

Thus, by the Morlet wavelet, we can construct a band-pass filter with a pass-band of $[f_0 - \beta/2, f_0 + \beta/2]$. Substituting the bandwidth β for the shape factor σ in Eq. (10), we can obtain a straightforward representation of the Morlet wavelet filter determined by the bandwidth β and center frequency f_0:

$$\Psi(f) = e^{-(2\ln 2/\beta^2)(f-f_0)^2} \tag{12}$$

Then, the Morlet wavelet filter can be implemented by:

$$WT(f_0, \beta) = F^{-1}\{X(f)\Psi^*(f)\} \tag{13}$$

Since the complex wavelet basis is employed to calculate the wavelet transform, the result of Eq. (13) is also an analytical signal. Therefore, the wavelet modulus is given by:

$$S(t) = \sqrt{[\mathrm{Re}(WT)]^2 + [\mathrm{IM}(WT)]^2} \tag{14}$$

Then, the MIE method is imposed on $S(t)$ to extract the impulses.

4. Parameter optimization of Morlet wavelet filter and flat SE

To ensure that the Morlet wavelet filter and flat SE can closely match the inspected signal, one must optimize the required parameters: namely the bandwidth β and center frequency f_0 of the wavelet filter, and the length M of the flat SE. For this purpose, a novel optimization rule is developed and illustrated as follows:

First of all, the optimization of the length of a flat SE can be converted into the problem of finding the actual IRP T by the following equation:

$$M = r \times T \tag{15}$$

According to Nikolaou's empirical rule--a flat SE with the length of 0.6-0.7 times the IRP can minimize the noise effects [5]--we typically choose r to be 0.6.

Let $p(i)$ be the impulse series extracted from the discrete vibration signal $f(i)$ by the joint method of the Morlet wavelet filter and MIE. As we know, defects of machine elements often generate a series of impact vibrations, the frequency of which is governed by the rotating speed and the geometry of the machine elements. The target of the joint method is to extract these fault-generated impulses as completely as possible. Therefore, the objective function of the optimization problem can be expressed as:

$$optimal(\beta, f_0, \hat{T}) = \max\left[\frac{N_p}{N_{\hat{T}}}\right] \tag{16}$$

Here, $N_{\hat{T}}$ is the expected number of the impulses under the IRP candidate $\hat{T}$, and it is obtained by $L/\hat{T}$, where L is the length of the signal; N_P is the number of the period impulses with an IPR of $\hat{T}$ in the impulse series $p(i)$. N_P is calculated through the following steps:

First, calculate the lengths of the interval $d(j)$ between the extracted impulses by the following equation:

$$d(j) = c(j+1) - c(j) \tag{17}$$

where the signal $c(j)$ is produced by the indices of the non-zero elements of the impulse series $p(i)$.

$$c(j) = find(p(i) \neq 0) \tag{18}$$

Then, N_P is obtained by the number of elements of the signal $d(j)$, which are close to the period $\hat{T}$.

$$N_p = sum(z) \tag{19}$$

where $z(j) = \begin{cases} 1 & if\ \dfrac{|d(j) - \hat{T}|}{\hat{T}} < tr \\ 0 & \end{cases}$.

Here, tr is a threshold value typically chosen as 0.05, in consideration of the slightly random fluctuation of the spacing between impulses in practical application.

To solve the problem expressed in Eq. (16), we should choose an appropriate optimization algorithm and consider a tradeoff between optimization accuracy and computation complexity. There are many methods available for global optimization, such as Genetic Algorithm (GA) [25], Simulated Annealing (SA) [26], Ant Colony Optimization (ACO) [27], etc. Among these algorithms, Genetic Algorithm is the most popular method. However, GA usually has two shortcomings: lack of good local search ability and premature convergence. In order to solve the problems of GA for global optimization, Differential Evolution (DE) was proposed by Stron and Price [18, 20]. Many studies have confirmed that DE is a more powerful optimization algorithm than GA, both in computation efficiency and accuracy [15, 19, 20, 28]. Therefore, DE is employed in this paper to solve the optimization problem shown in Eq. (16). The detailed introduction about DE can be referred to in Ref. [18] and Ref. [20]. There are several variations of DE algorithm. We use the *DE/rand/bin* –version in this paper, and its control parameters are chosen as follows: scaling factor F = 0.8, crossover ration CR = 0.8, number of population NP = 20, and maxima generation number G_{max}=50.

Finally, the steps of the proposed hybrid method are summarized as follows:

(1) Optimize the Morlet wavelet filter and flat SE simultaneously by DE algorithm based on the rule expressed in Eq. (16).

(2) Filter the vibration signal using the optimal wavelet filter to diminish interfering vibrations and noises, and then calculate the wavelet modulus of the filtered signal.

(3) Isolate the impulses in the wavelet modulus via the MIE method.

(4) Analyze the periodicity of the extracted impulses and fault identify.

5. Simulation study

5.1 Impulsive signal added with Gaussian noise

In this section, the signal shown in Fig. 4(a) is used to test the effectiveness of the proposed joint method. The optimal parameters are found as β= 2460 Hz, f_0= 6000 Hz, and T = 0.0248 S, which correspond to 40.32 in Hertz. The parameters f_0 and T obtained by the DE-based optimization algorithm are very close to the carrier frequency and IRP of the original impulsive signal, which demonstrates the effectiveness of the proposed optimization algorithm. With these parameters, the optimal Morlet wavelet filter and flat SE are constructed. Fig. 5 (a) is the wavelet modulus obtained by the wavelet filtering. Some impulses can be observed, but the noise is still heavy. Then, the MIE method is employed to further remove the noise and isolate the impulses. The extracted impulses are presented in Fig. 5(b), from which we can see that nearly all the impulses immersed in noise are picked out. By comparing Fig. 4(b) and Fig. 5(b), we can conclude that the proposed joint approach is much more effective and robust than the conventional morphological signal processing.

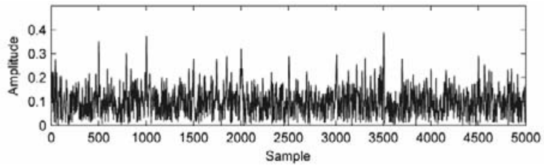
To further prove the superiority of the proposed method, we also processed the simulation signal using a wavelet threshold de-noising method proposed by Lin et.al. [3], in which Morlet wavelet is employed as the basic wavelet, and the threshold is determined by maximum likelihood estimation utilizing prior information on the probability density of the impulse. It is confirmed to be much more effective than the soft- and hard-thresholding rules in vibration signal de-noising. Its de-noising result is shown in Fig. 6. Though several true impulses are extracted, a lot of fake impulses also exist, which would affect the recognition of true impulses. On the contrary, the proposed joint approach isolates all the true impulses, and no fake impulses exist in the result [see Fig. 5(b)].

5.2 Impulsive signal tainted by sinusoidal interference and Gaussian noise

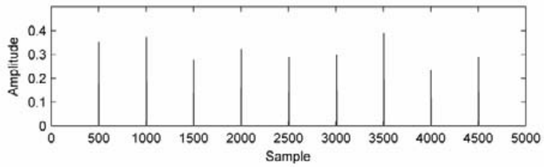
In this section, another simulated signal, which is seriously tainted by sinusoidal interference and Gaussian noise, is processed to evaluate the proposed method. The simulated signal is formulated as follows:

$$x(t) = x_1(t) + x_2(t) + x_3(t) \tag{20}$$

where x_1 (t) is the same impulsive series as that in Fig. 1(a); x_2 (t) is the sum of two harmonic waves: x_2 (t) = sin $(2\pi 100t)$ + 0.6cos $(2\pi 3000t)$; x_3 $(t)$is Gaussian noise. This simulated signal is shown in Fig. 7. We can see the original impulses are totally buried in the sinusoidal interferences and Gaussian noise. The de-noised result of the proposed joint method is displayed in Fig. 8, from which we can see all of the original impulses are extracted. For comparison, we also present the de-noising result of the MLE tresholding method based on wavelet transform. We can see it only extracts a partition of the original impulses, and too many fake impulses exist in Fig. 9. Therefore, the proposed approach can provide much better results.



(a)



(b)

Fig. 5. (a) The wavelet modulus obtained by adaptive Morlet wavelet filter; (b) the isolated impulses extracted by the adaptive Morlet wavelet filter followed by MIE method.

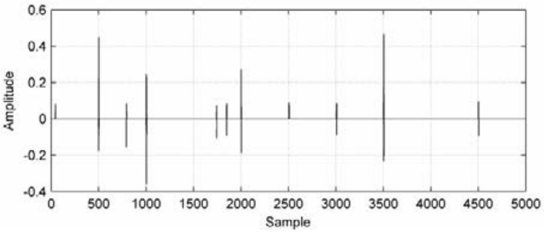


Fig. 6. De-nosing result of the signal shown in Fig. 4 (a) using wavelet-based MLE thresholding.

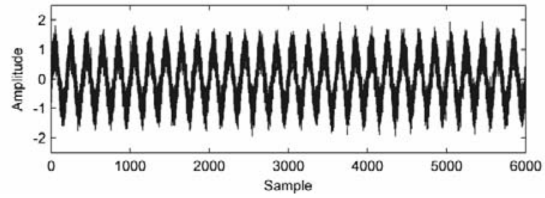
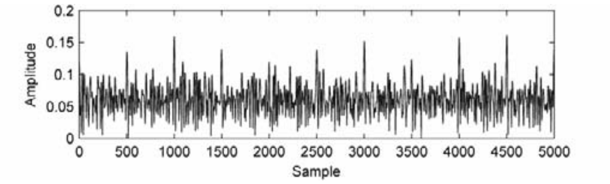


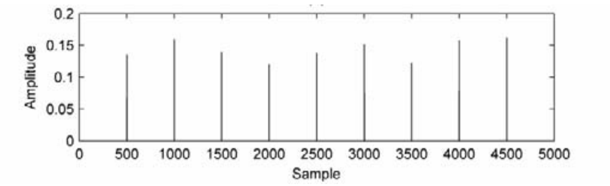
Fig. 7. The simulated signal shown in Fig. 1 (a) with Gaussian noise and sinusoidal interferences added.

6. Experimental validation

In this section, the proposed method is evaluated using the vibration data measured in our lab. The experiments were carried out using a machinery faults simulator as shown in Fig. 10. The bearings used in this test are N205 cylindrical roller bearings. Two typical bearing defects, outer race fault and inner race fault, were artificially produced by the electrical-discharge machining method and the defect size is



(a)



(b)

Fig. 8. (a) The wavelet modulus of the simulated signal shown in Fig. 7; (b) the isolated impulses extracted by the adaptive Morlet wavelet filter followed by MIE method.

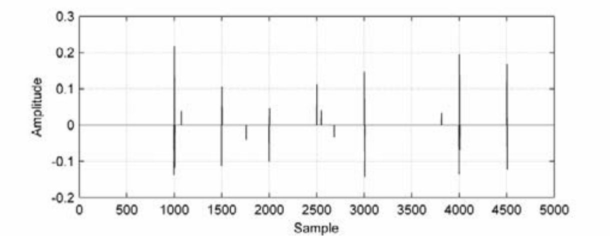


Fig. 9. De-nosing result of the signal shown in Fig. 7 using the wavelet-based MLE thresholding.

0.2mm×0.2mm (depth×width), as shown in Fig. 10. The signals were measured by an accelerometer mounted on the outer surface of the bearing case. The shaft's rotating speed is 1500 rev/min, and the sampling frequency is set to 20 kHz. By calculation, the Ball-Passing Frequency Outer-race (BPFO) is 124.7 Hz and Ball-Passing Frequency Inner-race (BPFI) is 175.3 Hz.

The signal of the bearing with an outer race defect is presented in Fig. 11(a). It is processed by the proposed joint approach and the result is shown in Fig. 11(b), from which we can see that periodical impulses buried in strong noise are extracted. The period of these impulses is approximately 0.0079 s, which is accordant with the BPFO. Therefore, we can identify that the bearing has an outer race fault.

Fig. 12(a) shows the vibration signal of the bearing with an inner race fault. No significant impulses can be observed in this signal. The proposed method is employed to isolate weak periodical impulses, and the de-nosing result is shown in Fig. 12(b). The period of the extracted impulses is approximately 0.00567 s, corresponding to the BPFI of 175.3 Hz.

To further validate the effectiveness of the proposed method, we apply it to two signals acquired from a different type of bearing under different test conditions. The signals are downloaded from the Case Western Reserve University (CWRU) bearing data center [29]. The bearings used in the two cases are 6205 deep groove ball bearings, and the rotating frequency and sampling frequency are 1772 rpm and 12 KHz,

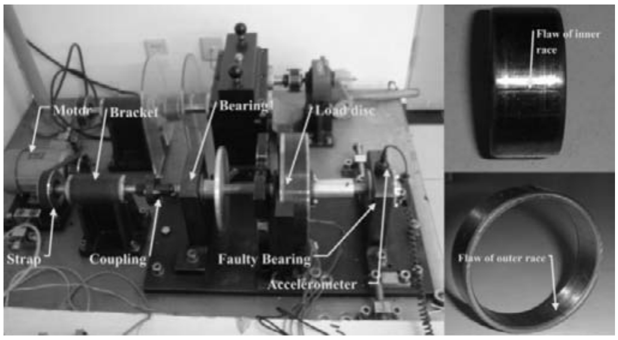


Fig. 10. Machinery faults simulator and defect bearings.

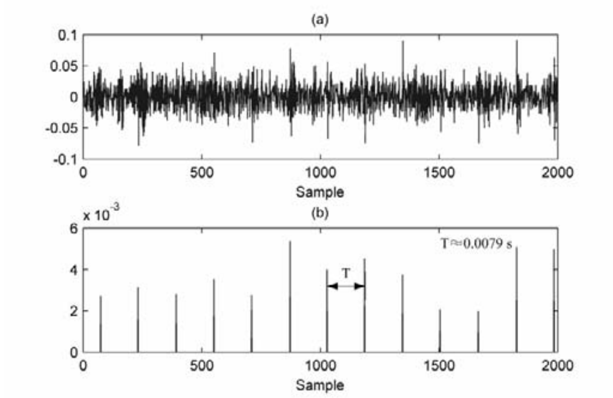
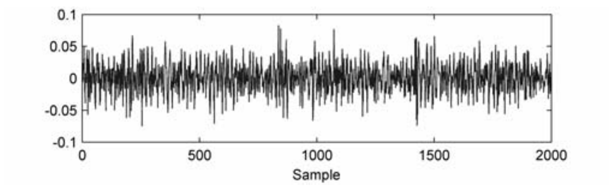
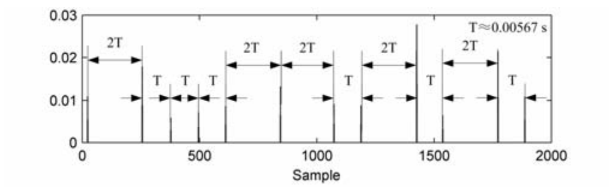


Fig. 11. (a) The vibration signal of the bearing with outer race fault; (b) The periodical impulses extracted by the proposed hybrid method.



(a)



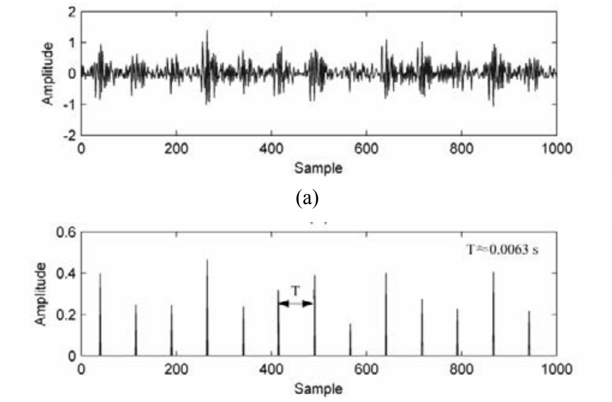
(b)

Fig. 12. (a) The bearing vibration signal of inner race fault. (b) The impulses extracted by the proposed method.

respectively.

The first signal to be analyzed is collected from a bearing with an inner race fault. The fault size is 0.007 inches×0.011 inches (width×depth). By calculation, the BPFI is 160 Hz. The raw signal and the extracted impulsive series are shown in Fig. 13(a) and (b), respectively. As shown in Fig. 13(b) , the period of the impulses is 0.0063 s, corresponding to the BPFI.

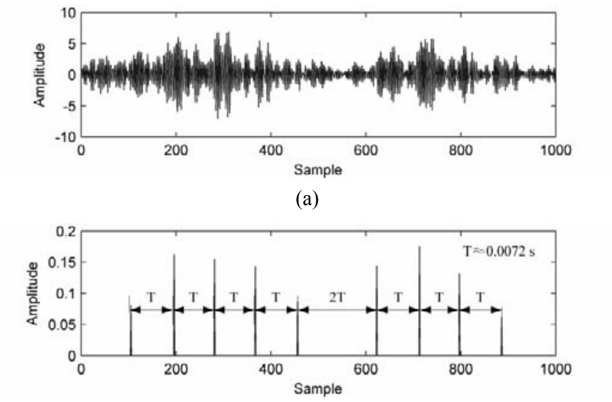
The second case to be studied is the signal of a bearing with a ball defect. The defect size is 0.028 inches × 0.011 inches (width×depth). The expected Ball Fault Frequency (BFF) is



(a)

(b)

Fig. 13. (a) The bearing vibration signal of inner race fault (downloaded from CWRU bearing center); (b) The extracted impulses using the proposed method.



(a)

(b)

Fig. 14. (a) The bearing vibration signal of ball fault (downloaded from CWRU bearing center); (b) The extracted impulses using the proposed method.

139 Hz. The original vibration signal and the isolated weak impulses are represented in Fig. 14(a) and(b), respectively. It can be seen that the pseudo-impulses produced by noise are removed and the real impulses generated by fault are extracted. The period of the impulses is 0.0072 s, corresponding to the BFF.

From these four applications, we can see that the joint method of Morlet wavelet filter and morphological impulse extraction is highly capable of extracting impulses from vibration signals with heavy noise. This makes the method very suitable for engineering applications.

7. Conclusions

In this paper, a new method is proposed to extract weak periodical impulses from the vibration signals with heavy background noise. The algorithm involves a wavelet filtering step prior to morphological signal processing. The main purpose of wavelet filtering is to remove interfering vibration signals and strengthen impulsive features. The second step, namely morphological signal processing, is then conducted to the filtered signal to isolate periodical impulses. To gain an excellent joint method, a novel scheme based on differential evolution is developed to optimize the wavelet parameters and flat SE. The main idea of the optimization algorithm is to find the parameters, which can extract the most amount of periodical impulses. The proposed method has been applied to simulated signals as well as vibration signals acquired from bearings under different conditions. The results have shown that the proposed approach is very effective in the extraction of weak periodical impulses under heavy noise, and its performance is much better than the traditional morphological processing and the wavelet-based MLE thresholding method. However, the proposed method is specially designed for period impulses isolation, so it is only applicable to fault diagnosis of rotating machines under stationary condition. Our future work will focus on how to extract the impulses generated under nonstationary operating conditions.

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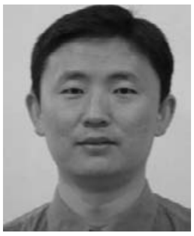

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