Morphological filter optimized by particle swarm optimization for noise removal

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The vibration signals collected from the bearing are often severely polluted by various noises. The removal of noise is a challenging problem in bearing fault diagnosis. To avoid using the time-consuming methods such as Fourier transform, wavelet, et al. And to extract the feature of rolling bearing effectively, a new method based on the mathematical morphological filter optimized by particle swarm optimization algorithm (PSO) is proposed in this paper. Firstly , the morphological filter's structure element (SE) is optimized by PSO and the signal-to-noise ratio (SNR) is used as a criterion to make up the fitness function. The optimal SE is used to construct the filter. The proposed method is evaluated by simulated signals and vibration signals measured from bearings with faults, respectively. Results show that the method can effectively remove the noise. So the method is an efficient tool for bearings noise removal.

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1. Introduction

Rolling bearings are widely used in rotating machinery. Unexpected bearing faults could cause unscheduled downtime and loss. But, the collected vibration signals are often severely polluted by various noises [1], which prevents the detection of bearing faults, so an effective signal processing method is necessary to remove the noise. There are many methods for filtering the noise, but they have different shortcomings [2, 3].

Recently, the mathematical morphological filter has been introduced into the fault diagnosis of machinery [4]. It 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. However, there also exists deficiency of the method that should not be overlooked. Such as how to select the SE, many paper used the SE through fixed selection [5, 6]. SE can decide the shape of the filter and determine the performance of morphological filter. We should select the SEs according to the characteristics of different noises. In this article we introduce the PSO algorithm to optimize the SE and construct an effective morphological filter.

The rest of this paper is organized as follows: In Section 2, the relevant background of morphology is described and the character of it is discussed. The PSO algorithm is used to optimize the SE. Then, in Section 3, the proposed method is validated by simulation data, which are composed of the impulse with noise and the random signal with noise. Additionally, in Section 4, we present practical examples to testify the applicability and efficiency of the optimal mathematical filter for removing the noise. Then, conclude this work in Section 5.

2. Relevant background

2.1 The fundamental theory of morphological filter

Morphological filter requires less computational time than other traditional filters. Through constantly moving the SE to match the signal, the purposes of de-noising can be achieved. The transformation consists of four basic operations: erosion, dilation, opening and closing operation [7]:

$$A \oplus B = \{z \in Z^n : z = a + b, a \in A, b \in B\} = \bigcup_{b \in B} (A)_b \quad (1)$$

$$A \Theta B = \{z \in Z^n : z = a - b, a \in A, b \in B\} = \bigcap_{b \in B} (A)_{-b} \quad (2)$$

$$A \circ B = (A \Theta B) \oplus B \quad (3)$$

$$A \bullet B = (A \oplus B) \Theta B \quad (4)$$

In formula, $\oplus$, Θ, $\circ$, $\bullet$ symbol corresponds to the dilation, erosion, opening and closing operation.

2.2 Design of morphology filter

Supposing the original signal $f(x)$ is a discrete function defined on D_f boundary and the structural element $g(x)$ is a discrete function defined on D_g boundary, the form of open - closing and close-opening filters are as follows[8]:

$$F_{OC}(f(x)) = (f \circ g \bullet g)(x) \tag{5}$$

$$F_{CO}(f(x)) = (f \bullet g \circ g)(x) \tag{6}$$

The morphological filter removes the positive and negative noise by constructing a form of open - closing and close- opening operation. But the opening operation leads to the contraction of the output of the open - closing operation and the closing operation leads to the expansion of the output of the close -opening operation, so there is something wrong about the value. Which directly affect the effort of the morphological filter. In order to avoid this problem, we construct the nonlinear filter in the form:

$$y(x) = \frac{1}{2}[F_{CO}(f(x)) + F_{OC}(f(x))] \tag{7}$$

2.3. Design and optimization of SE

In order to get the optimal SE, the following should be considered:

1. The size of the SE.
2. The amplitude of the SE.

The size of the SE relies on the period length of the noise. In order to determine the range from which the size of the SE is chosen, the period length of the noise is estimated before carrying out the optimization. The size of the SE is chosen from 3*3 to (2*L/2+1)*(2*L/2+1), where L is the estimated length of the noise period[9]. It is observed that the empirical rule for a SE length around 0.6 times the pulse repetition period is verified. And the length of the noise is usually very short, so we choose a size of the SE from 3* 3, 5* 5, 7* 7, 9* 9.

In most paper, the amplitudes of the SE were usually selected as zero. They were selected because they present the most simple SE with a straightforward application, but different signals mixed with different noises, and we should construct different SEs to match them, in this paper, we get the amplitude of the SE through optimization according to different noises.

2.4. The optimization of morphological filter

Now there are many optimal algorithms e.g., genetic algorithm (GA), ant colony algorithm, particle swarm optimization algorithm (PSO) and so on. PSO based on the theory of swarm intelligence which is similar to GA but it searches the optimal particle in the whole space and doesn't achieve optimization through evolution. Compared with the GA and ant colony, the PSO is easy to implement and is an effective global optimization algorithm. PSO searches the space in the n-dimensional through the change of the position and the speed to find the optimal solution of the current population. Therefore, we choose the PSO to optimize the SE of the morphological filter. In the process of optimization, each individual (particle) adjusts its flight speed and position according to the following formula [10]:

$$v_{ij}(t+1) = wv_{ij}(t) + c_1 r_{1j}(p_{ij}(t) - x_{ij}(t)) + c_2 r_{2j}(p_{g_j}(t) - x_{ij}(t)) \tag{8}$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \tag{9}$$

where the subscript "i" represents the i th particle. "j" represents the *j*-dimensional. The subscript "t" represents the t generation. $v_{ij}(t)$ is the velocity of the i th particle in the t th iteration; $x_{ij}(t)$ is the position of the i th particle; $p_{ij}(t)$ is the pbest position of the i th particle; p_{gj} is the gbest position of the particles in the whole space; The w represents the inertia weight. c_1、 c_2 are learning factors. $r_1 \sim U(0,1)$, $r_2 \sim U(0,1)$ represent two independent random functions.

2.5. Determination of the fitness function

The signal-to-noise ratio (SNR) is selected as the fitness function. The function is defined in the form:

$$R_{SN}(x) = 10\lg\frac{p(w)}{N(w)} \;;\; p(w) = |Y(w)|^2 \tag{10}$$

where $R_{SN}(x)$ is the SNR function of the system, $y(x)$ is the output of the filter, $Y(w)$ is the power spectrum of the output signal; $N(w)$ is the power spectrum of the noise.

The process of optimizing the SE based on the PSO is given below:

(1)At the beginning of the optimization process, randomly initialize positions and velocities, pbest, gbest of the particles;

(2) Set the parameters of SEs equals the parameters of the particles' positions;

(3) Use the SEs to construct the morphological filters;

(4) Use the morphological filters to removal the noise, then calculate the current fitness value $f(x_i)$ of each particle;

(5) Use the pbest to construct the morphological filter and calculate the fitness value $f(x_p)$, then Compare the $f(x_p)$ with $f(x_i)$. If $f(x_i)$ is greater than $f(x_p)$, then set the parameters of the current position X_i to the pbest;

(6) Use the gbest to construct the morphological filter and calculate the fitness value $f(x_g)$ and compare the $f(x_p)$ with $f(x_g)$. If $f(x_p)$ is greater than $f(x_g)$, then set the parameters of pbest to the gbest;

(7) For each particle i in the swarm, Calculate positions x_{i+1}, velocities v_{i+1} using Eq. (8)and (9);

(8) While the termination conditions are not met, return to step (3);

(9) End loop.

3. The validation through simulation data

3.1. Simulation of random signal

In order to validate the de-nosing effort of the optimal filter (through optimization the size of the SE is 5* 5, the amplitudes of the SE are (0.0486, 0.0274,-0.0137, 0.0274, 0.04212)). This paper simulated a random signal, which is formulated as follows (the sampling frequency is 1000 Hz and the sampling time is 1 s):

$$x(t) = x_1(t) + x_2(t) \tag{11}$$

where $x_1(t)$ is a heaviside wave: $x_1(t) = (1 - 0.8 \cdot \mathrm{u})\sin(2\pi \cdot 50t)$, u is the function make the heaviside step ; $x_2(t)$ is the Gaussian noise(SNR=13.57dB), then compared the effort with the morphological filter of flat SE (The size of the SE is 5* 5, the amplitudes of the SE are (0, 0, 0, 0, 0)) [5, 6]. And the wavelet of optimal Morlet ($\varphi(t) = \exp(-\beta^2 t^2 / 2)\exp(j2\pi\ f_0 t)$, the optimal parameters β =0.3, $f_0 = 5\mathrm{Hz}$)[11] .Then the results are showed in Fig. 1. Among them, the parameters of the PSO are setted as showed in Table 1:

Items	Values of parameters
Population scale	20
Terminal interaction times	300
Search space dimension	5
cognitive factor	1.2
social learning factor	1.2
Maximum inertia weight	1
Minimum inertia weight	0.3
Minimum value change among 5th	0.01

Table 1． The control parameters of PSO for optimizing the morphological filter.

The root mean square error criterion (RMSE) is used for the performance evaluation of the different methods in noise removal, which is expressed as formula(12):

$$\mathrm{RMSE}=\sqrt{\sum(\hat{x}(t) - x(t))^2 / T} \tag{12}$$

where $\hat{x}(t)$ denotes the purified signal, $x(t)$ denotes the original signal without noise, and T is the length of time series.

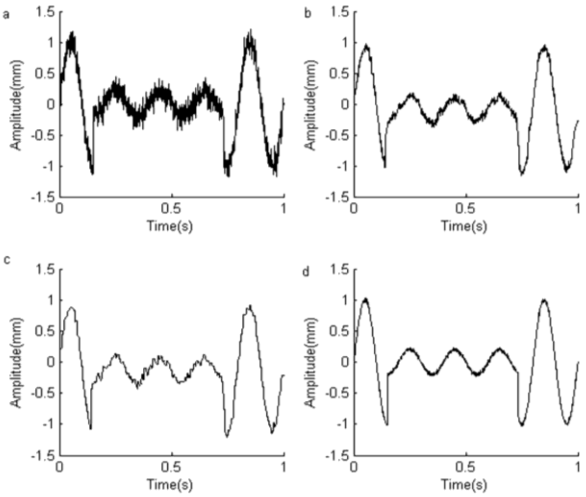

Fig. 1. Comparison of de-noised results obtained by optimal filter, the morphological filter of flat SE，the wavelet of Morlet, for the random signal (a)the original signal ,(b)the purified signal by the wavelet of Morlet, (c) the purified signal by the morphological filter of flat SE,(d)the purified signal by the optimal filter.

Methods	RMSE(%)
The optimal filter	0
The morphological filter of flat SE	12%
The wavelet of Morlet	15%

Table 2．The performance evaluation of the different methods in noise removal.

From the results we can get that the morphological filter of flat SE and the optimal Morlet wavelet can filter out most of the noise, but there is still some noise superimposed in the signal. The optimal morphological filter is more effective in de-nosing. It is known that there are usually a lot of random signals with noises in the machinery equipment. Through the optimal filter, the noises in the random signals were effectively removed.

3.2. Simulation and analysis of the impulse signal

In the machinery, there are usually a series of impulse mixed with the noise, so the simulated signal is formulated as follows (the sampling frequency is 1000 Hz and the sampling time is 1 s):

$$x(t) = x_1(t) + 2x_2(t) + x_3(t) \tag{13}$$

where $x_1(t)$ is the sum of three harmonic waves: $x_1(t) = 0.8\sin(2\pi \cdot 10t) + \sin(2\pi \cdot 30t) + 0.3\sin(2\pi \cdot 45t)$; $x_2(t)$ is $\sin(2\pi t)$; $x_3(t)$ is the Gaussian noise(SNR= 16.54dB). In order to verify the de- noising effect of the optimal filter (the size of the SE is 3* 3, the amplitudes of the SE are (0.0032, 0.0151, 0.0031)). Then the de- noising results of the optimal filter were compared with the morphological filter of flat SE(The size of the SE is 3* 3, the amplitudes of the SE are (0,0,0)). And the wavelet of Morlet (the optimal parameters β =0.5, $f_0 = 1\mathrm{Hz}$). Then the results are showed in Fig. 2. Among them, the parameters of the PSO are setted as follows:

Items	Values of parameters
Population scale	20
Terminal interaction times	300
Search space dimension	3
cognitive factor	1.2
social learning factor	1.2
Maximum inertia weight	1
Minimum inertia weight	0.3
Minimum value change among 5th	0.01

Table3. The control parameters of PSO for optimizing the morphological filter.

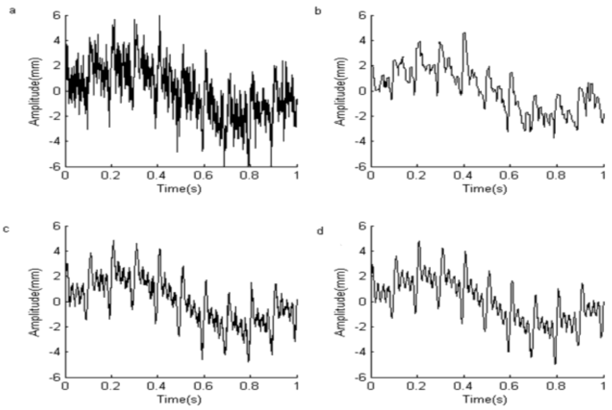

Fig. 2. Comparison of de-noised results obtained by optimal filter, the morphological filter of flat SE，the wavelet of Morlet, for the impulse signal (a)the original signal , (b) the purified signal by the morphological filter of flat SE, (c)the purified signal by the wavelet of Morlet, (d) the purified signal by the optimal filter.

Methods	RMSE(%)
The optimal filter	0
The morphological filter of flat SE	16%
The wavelet of Morlet	9%

Table 4. The performance evaluation of the different methods in noise removal.

From the results we can get that the optimal morphological filter effectively extracted the impulse signal and removed the noise. The morphological filter of flat SE and the Morlet wavelet can eliminate the most of the noise, but there is still a certain noise reserved, which can result in the loss of the useful information.

4. Experimental validation

The proposed method is applied to bearing fault signals obtained from the Case Western Reserve University [12]. The bearing type in the experiments is SKF 6205-2RS JEM. Experiments were conducted by using a 2 hp reliance electric motor. Bearings were seeded with faults by using electro-discharge machining. Faults were 0.021 inches in diameter and 0.011 inches in depth and were introduced at the inner raceway, rolling element (i.e. ball) and outer raceway. Motor speeds of 1797 RPM. Data were collected at 12,000 samples/second.

The fault signals are mashed with a lot of impulse, random signals and noise. In order to verify the de-noising effect of the optimal filter (the size of the SE is 9* 9, the amplitudes of the SE are (0 , 0.0375, 0.075 0, 0.112 5,0.150, 0.112 5,0.075 0,0.037 5,0)). Then the de-noising results of the optimal filter were compared with the morphological filter of flat SE(The size of the SE is 9* 9, the amplitude of the SE is (0, 0, 0, 0, 0, 0, 0, 0, 0)). And the wavelet of Morlet(the optimal parameters β =0.5, $f_0 = 0.5\text{Hz}$) , the fault signals of inner and outer rings were used to be de-noised .Filtering results are shown in Figs 4, 5.

Items	Values of parameters
Population scale	20
Terminal interaction times	400
Search space dimension	9
cognitive factor	1.2
social learning factor	1.2
Maximum inertia weight	1
Minimum inertia weight	0.3
Minimum value change among 5th	0.001

Table5. The control parameters of PSO for optimizing the morphological filter.

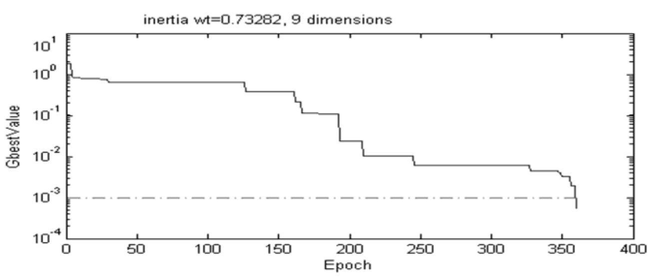

Fig. 3. The curve of the PSO optimization process.

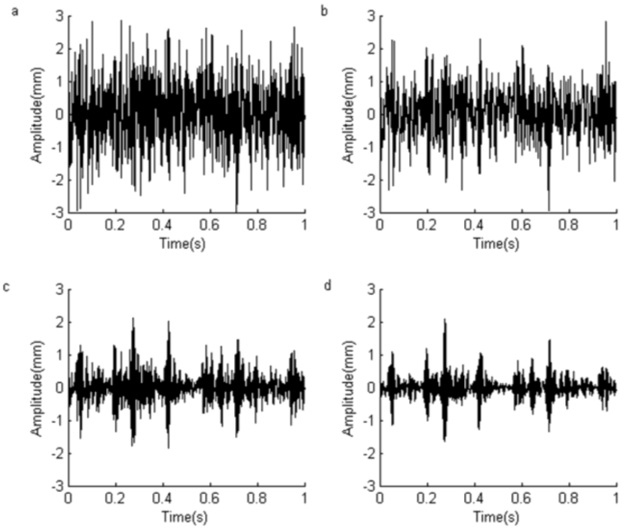

Fig. 4. Comparison of de-noising results obtained by the optimal filter, the morphological filter of flat SE, the wavelet of Morlet, for the vibration signal of a roller bearing with an inner-race fault (a)the original signal ,(b) the purified signal by the wavelet of Morlet,(c) the purified signal by the morphological filter of flat SE , (d) the purified signal by the optimal filter.

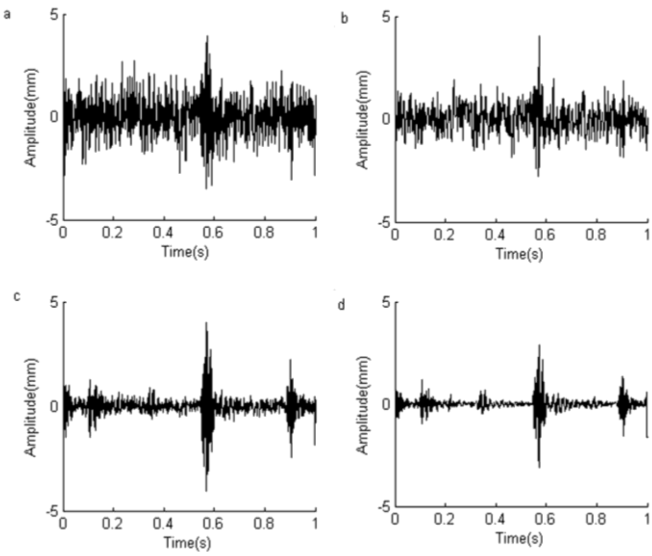

Fig. 5. Comparison of de-noising results obtained by the optimal filter, the morphological filter of flat SE, the wavelet of Morlet, for the vibration signal of a roller bearing with an outer-race fault (a)the original signal ,(b) the purified signal by the wavelet of Morlet,(c) the purified signal by the morphological filter of flat SE , (d) the purified signal by the optimal filter.

From the results we can get that the optimal filter works very well in de-noising and effectively shows the impact within and outside the bearing.

5. Conclusions

In order to extract the feature and diagnose the fault of bearing, this article introduced the morphological filter as a method for noise removal. But there are various types of fault signals, which require that we construct the morphological filter according to the character of the noises, so we proposed the PSO algorithm to optimize the SE and used the adaptive optimal SE to construct the morphological filter. Moreover, since the SE is optimized by the PSO according to the characteristics of the noise, so it can effectively remove the noise.

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