Rotating machinery weak fault signal detection method based on QPSO and stochastic resonance

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Abstract. Due to the weak early vibration signal of rotating machinery, which is nonlinear and non-stationary, the traditional filtering method has some limitations. To this end, a weak signal detection method combining Quantum Particle Swarm Optimization (QPSO) and Stochastic Resonance (SR) is proposed. First, according to the adiabatic approximation theory, make the original signal meet the SR requirements, and optimize the structural parameters of the SR through QPSO; secondly, the signal-to-noise ratio is used as the objective function to make the input signal and the output signal achieve the best match; finally, simulation and experimental data are used to verify the feasibility of the proposed method. Comparative analysis shows that the proposed method increases the amplitude by 46% compared with the characteristic frequency obtained by the PSO optimized SR model.

1. Introduction

Bearings, gears, drill bits, and other rotating machinery are the core components of the equipment. With the accumulation of time, they will experience varying degrees of aging, wear, and even failure. If these early faults are not diagnosed in time, it will cause major economic losses and reduce production efficiency. Considering that the early fault signal of the equipment is weak, it is difficult to realize the feature extraction of the early fault. Traditional noise reduction methods are based on the form of filtering, such as fast Fourier transform, wavelet noise reduction, Wigner-Ville distribution, these methods can suppress the useful signal to a certain extent while suppressing the noise [1-3], which is not conducive to the extraction of fault features. With the development of nonlinear dynamics and interdisciplinary science, stochastic resonance (SR) has been widely used in many fields such as geophysics, biology, medicine, and so on [4-5].

The SR method is different from the traditional signal processing method. It transfers the energy in the noise to the characteristic signal to enhance the amplitude of the characteristic signal. Therefore, it has received extensive attention in the field of weak fault feature extraction [6-7]. Among them, Ren et al. [8] preprocessed the early weak signal of the faulty bearing through the SR method, which reduced the influence of noise on the characteristic frequency, and extracted the fault characteristic sets in the time domain, frequency domain, and time-frequency domain for fault diagnosis, verified the high efficiency of SR on weak signal preprocessing. Wang et al. [9] solved the problem of low signal-to-noise ratio of the system when the traditional SR reaches output saturation by improving the quartic
potential function that restricts particle motion in the classic bistable SR into a piecewise quadratic bistable potential function. The above research analyzes that SR has the effect of enhancing the signal amplitude, but it does not analyze the influence of structural parameters on the SR system. Taking into account the influence of the structural parameters of the SR system on the resonance effect, Jiang et al. [10] used the idea of sub-sampling frequency conversion to process large-parameter signals to meet the requirements of SR and combined the bat algorithm with the SR method to solve traditional genetic algorithms and swarm intelligence algorithms are easy to fall into the problem of minimum value, which enhances the amplitude of the characteristic frequency. Wang et al. [11] used the artificial fish school algorithm (AFSA) to optimize the structural parameters of the cascaded SR, which reduced the interference of noise on the characteristic frequency and solved the problem of difficult diagnosis of bearing faults in the aero-engine rotor system. Ge et al. [12] optimized the structural parameters of SR through a quantum genetic algorithm, which improved the signal ratio during early fault diagnosis of bearing and highlighted the characteristic frequency. However, in the above research, there are many parameter settings in the optimization algorithm, and too many parameter settings will affect the optimization performance of the algorithm.

To solve the above problems and take into account the shortcomings of traditional SR in detecting weak signals, this paper combines the QPSO algorithm [13] with the SR model to construct an adaptive SR model. By introducing quantum states into the traditional PSO, this optimization of the structural parameters of the SR system solves the problem that the system is easy to fall into a local optimal solution, and improves the signal-to-noise ratio of weak signal output.

2. SR model and signal-to-noise ratio

The earliest SR was established based on the Langevin equation. According to the adiabatic approximation theory, SR is only suitable for signals with small parameters. Assuming that the input noise is a positive rotation signal with Gaussian white noise, the SR equation is expressed as [14]:

\[ \dot{x} = -U'(x) + s(t) + n(t) \]  

where \( n(t) \) is Gaussian white noise with a mean value of zero, \( s(t) \) is the input signal, and \( U(x) \) is the potential function of the nonlinear system, where the expression of the potential function is as follows:

\[ U(x) = \frac{a}{2} x^2 + \frac{b}{4} x^4 \]  

In the formula, parameters ‘a’ and ‘b’ are the structural parameters of the system, and both are greater than zero, and the white noise satisfies the following formula:

\[ n(t) = \sqrt{2D} \xi(t) \]  

\( D \) is the intensity of noise, \( \xi(t) \) is Gaussian white noise with a mean value of 0 and a variance of 1. The input signal satisfies the following periodic signal:

\[ s(t) = A \sin(2\pi f_0 t) \]  

Input Formulas (2) - (4) into Formula (1) to obtain the following bistable stochastic resonance model:

\[ \dot{x} = ax - bx^3 + A \sin(2\pi f_0 t) + n(t) \]  

According to Formula (5), the movement of particles is controlled by the synergy of an input signal, noise, and nonlinear system. When the noise signal is zero, it is difficult for the particles to cross the potential barrier and move periodically between the potential wells. However, the height of the barrier is \( \Delta V = a^2/4b \). Observation shows that the structural parameters of the nonlinear system are very important to the movement of particles. Therefore, for any input signal, there must be optimal structural parameters to achieve the best resonance effect. This paper selects the signal-to-noise ratio (SNR) as the objective function to evaluate the performance of ASR. The definition of SNR is as follows:
\[ SNR = 10 \log \left( \frac{S(f_0)}{N(f_0)} \right) \]  

In the formula: \( f_0 \) is the signal frequency, \( S(f_0) \) is the signal power, and \( N(f_0) \) is the noise power.

### 3. Optimization of system structure parameters

#### 3.1. The impact of system parameters on SR

The barrier height \( \Delta V \) is jointly determined by the structural parameters ‘a’ and ‘b’ of the SR model. Changing the structural parameter ‘a’ or the parameter ‘b’ alone, or simultaneously changing the parameters ‘a’ and ‘b’, can achieve the transformation of the barrier height. The lower the potential barrier, the lower the required input signal and noise intensity, and vice versa. At present: There are two main ways to adjust the SR system: 1) for a constant input signal, ensure that the structural parameters of the system remain unchanged. By enhancing the intensity of noise, the phenomenon of "resonance" is achieved. However, the change in noise intensity has certain shortcomings, the noise intensity can only be increased but not decreased. 2) When the noise intensity is constant, the purpose of enhancing the weak signal is achieved by adjusting the structural parameters of the system.

Considering that in actual engineering, the environment is complex and changeable, and the intensity of the input signal and noise are difficult to calculate. Therefore, the system can achieve resonance by optimizing the structural parameters ‘a’ and ‘b’ of the SR system.

#### 3.2. QPSO algorithm

In the traditional PSO algorithm, the position change of the particles is relatively fixed, lacking randomness, and easy to fall into the local optimum. Given the shortcomings of the PSO algorithm, the quantum state is introduced into a PSO algorithm, which does not consider the direction of particle movement and increases the randomness of particle position movement. The key point of QPSO [13] is to introduce the concept of \( m_{\text{best}} \), and the calculation formula is as follows:

\[ m_{\text{best}} = \frac{1}{s} \sum_{i=1}^{s} P_{\text{local}_i} \]  

The process of particle position update is as follows:

\[
\begin{align*}
  p_{k+1}^i &= \varphi \cdot p_k^i + (1-\varphi) p_k^g \\
  x_{k+1}^i &= p_{k+1}^i + \lambda \left[ m_{\text{best}} - x_k^i \ln \frac{1}{u} \right]
\end{align*}
\]  

Among them, \( \varphi \) and \( u \) is the uniform distribution of \((0,1)\); \( \lambda \) is the only control parameter. The pseudocode for QPSO is shown in Table 1.

The implementation steps of QPSO are as follows:

Step1: Initialize the position of the particles in the particle swarm, and calculate the average optimal position of the particle swarm according to Formula (7).

Step2: Calculate the fitness value of each particle and compare it with the previous fitness value. If the current fitness value is greater than the fitness value of the previous iteration, it will be taken as the current best extreme value.

Step3: Calculate the current global optimal position of the group.

Step4: Compare the current global optimal position with the global optimal position of the previous iteration, and judge whether the global optimal position of the particle needs to be updated.

Step5: Calculate the position of a random point and the new position of the particle by Formula (8).

Step6: Repeat the above steps until certain loop constraints are met.

The flowchart of the QPSO algorithm is shown in Figure 1.
Table 1. Pseudocode for QPSO.

| Algorithm |
|-----------|
| Initialize position $X_i$ for particle $i$ |
| Calculate the optimal position of particle swarm average by Formula (7) |
| Evaluation particle $i$ and set $p_{Besti}=X_i$ |
| $g_{Best}=\max\{p_{Best}\}$ |
| While ($t<T_{max}$) |
| for each particle |
| Update the velocity and position of particle $i$ by Formula (8) |
| end for |
| Evaluation particle $i$ |
| if $fit(X_i)>fit(p_{Best})$ |
| $p_{Best}=X_i$; |
| if $fit(p_{Best})>fit(g_{Best})$ |
| $g_{Best}=p_{Best}$ |
| End while |
| Return $g_{Best}$ |

**Figure 1.** Flow chart of QPSO.

4. Simulation analysis
To verify the efficiency of the proposed method, a simulation experiment is carried out with a positive rotation signal with Gaussian white noise. According to the adiabatic approximation theory, the sampling frequency of the simulated signal is set to 5Hz, Gaussian white noise with a SNR of -10db is added, and the input signal is $s(t) = 0.5 \sin(0.04\pi t)$.

Perform time-domain waveform and FFT spectrum analysis on the simulated signal. The results are shown in Figure 2. From the time-domain waveform diagram, it is difficult to find periodic components and perform FFT spectrum analysis on them. Due to the influence of the transmission
path and external noise interference, the peak value at the characteristic frequency of the simulated signal is not clear and difficult to observe.

Figure 2. Simulation signal with noises: (a) Time-domain waveform (b) FFT spectrum analysis.

To highlight the characteristic frequencies, the QPSO method is used to optimize the structural parameters of the SR model (a=0.056, b=0.03). The number of iterations is 100 and the population is 30. Use the method proposed in this article to analyze the time-domain waveform and FFT spectrum of the original signal, and the result is shown in Figure 3. It is observed that the time-domain waveform graph has obvious periodicity, the characteristic signal in the FFT spectrum is prominent, and the amplitude of the characteristic signal is about 0.19. The results show that the proposed method has a certain degree of efficiency in detecting weak signals.

Figure 3. The proposed SR (a=0.056, b=0.03) output: (a) Time-domain waveform (b) FFT spectrum analysis.

Figure 4. Fixed-parameter SR (a=1, b=1) output: (a) Time-domain waveform (b) FFT spectrum analysis.

Figure 5. PSO-SR method output: (a) Time-domain waveform (b) FFT spectrum analysis.

To verify the advantages of the method proposed in this paper, the method proposed in this paper is compared with two methods (traditional SR model (a=1, b=1) [15], particle swarm optimization SR model [16]). Figures 4 and 5 show the time-domain waveforms and FFT spectrum of the traditional
SR model and the PSO-SR model. Comparing Figures 3-5, we can see that although the fixed-parameter SR can also detect weak signals to a certain extent, the amplitude of the FFT spectrum enhancement characteristic signal is limited, about 15% of the amplitude when the proposed method is used for weak signal detection; Figure 5 shows the use of PSO to optimize the structural parameters of the SR model. Observing the time-domain waveform and FFT spectrum, it can be seen that the SR model optimized by PSO has a characteristic signal amplitude of 0.13 when detecting weak signals. Compared with the PSO-SR method, when the method proposed in this paper performs weak signal detection, the amplitude of the characteristic signal is increased from 0.13 to 0.19, and the amplitude is increased by 46%.

5. Experimental verification
To verify the effectiveness of the proposed method, the experimental data of the bearings of Western Reserve University is used for analysis [14]. The experimental equipment is shown in Figure 6. During the experiment, the bearing with the inner ring failure is selected for the experiment, and the fault size is 0.007in. The speed is 1797rpm, the motor load is 0hp, the pitch circle diameter and the rolling element diameter of the tested bearing are 39mm and 7.9mm, respectively, the number of rolling elements is 10, and the contact angle is 0 degrees. The simulation analysis shows that the amplitude of the characteristic signal is mainly displayed by the spectrogram. Therefore, the following experiments analyze the original signal and the spectrogram processed by the proposed method.

Performing frequency spectrum analysis on the original test data, the result is shown in Figure 7. Due to the interference of external noise, it is difficult to highlight the characteristic frequency of the fault signal. To suppress the interference of noise on the fault characteristics, the original signal is processed by the method proposed. Taking into account that the SR model needs to meet the requirements of small parameters, the signal compression ratio of the original signal is set to 2000, the original vibration signal is input into the QPSO optimized SR model, and the output result is analyzed by FFT, and the result is shown in Figure 8. Observing the frequency spectrum shown in Figure 8, it is obvious that the fault characteristics are highlighted, which verifies the feasibility of the proposed method in suppressing noise and highlighting characteristic frequencies. To highlight the efficiency of the proposed method, the PSO optimized SR model is used to process the original signal and conduct a comparative analysis. The frequency spectrum of the vibration signal processed by the PSO optimized SR model is shown in Figure 9. The comparison found that although the optimized SR model of PSO can suppress noise and highlight the characteristic frequency, the effect is not as good as the QPSO algorithm.

Figure 6. Experimental platform.

Figure 7. Frequency domain diagram of the original signal.

Figure 8. Spectrum diagram of the QPSO-SR output.
6. Conclusions
This paper proposes a weak signal detection method combining the quantum particle swarm algorithm and stochastic resonance. By transferring the energy in the noise to the characteristic frequency, the shortcomings of traditional filtering methods are solved. Simulation analysis shows that when using stochastic resonance to detect weak signals, compared with the SR structure parameters optimized by PSO, the proposed method increases the amplitude of characteristic signals by 46% when detecting weak signals. The simulation verifies the superiority of the method proposed in this paper. The method proposed in this paper is applied to the detection of faulty bearings, and it is verified that the proposed method can suppress noise interference and detect early weak signals.

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