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A Fault Feature Extraction Method Based on Second-Order Coupled Step-Varying Stochastic Resonance for Rolling Bearings

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Featured Application: The fault feature extraction method can be applied in health monitoring of rolling bearings.

Abstract: In mechanical equipment, rolling bearings analyze and monitor their fault based on their vibration signals. Vibration signals obtained are usually weak because the machine works in a noisy background that makes it very difficult to extract its feature. To address this problem, a second-order coupled step-varying stochastic resonance (SCSSR) system is proposed. The system couples two second-order stochastic resonance (SR) systems into a multistable system, one of which is a controlled system and the other of which is a controlling system that uses the output of one system to adjust the output of the other system to enhance the weak signal. In this method, we apply the seeker optimization algorithm (SOA), which uses the output signal-to-noise ratio (SNR) as the estimating function and combines the twice-sampling technology to adaptively select the parameters of the coupled SR system to achieve feature enhancement and collection of the weak periodic signal. The simulation and real fault data of a bearing prove that this method has better results in detecting weak signals, and the system output SNR is higher than the traditional SR method.

Keywords: strong noise; SCSSR; weak signals; SNR; SOA

1. Introduction

Rolling bearings are widely used in the field of engineering machinery. It is one of the parts with the highest failure rate, and causing problems in regard to quality and safety [1]. The fault monitoring and analysis of bearings usually deals with the vibration signals collected by sensors [2–4]. When the background noise of the vibration data is high and the signal-to-noise ratio (SNR) is low, it is very challenging to obtain the bearings' fault features. In the context of loud noise, the traditional bearing fault analysis methods usually start with noise reduction [5–10]. Although these methods can reduce the noise, they also can weaken the effective characteristic signal [10–18].

Benzi et al. [19] proposed the theory of stochastic resonance (SR), which can pass noise to weak signals and strengthen the weak characteristic signals submerged in them [20]. This feature has aroused great interest as more and more scholars have begun to study the impact of SR on machine fault diagnosis [21–30] and its application in other fields [31–41]. In order to quantitatively describe the phenomenon of SR and have a standard for judging the effect of SR, a measurement index is

required. In this paper, SNR is used as a measure of SR [42]. When the SNR is larger, it means that the signal has less noise interference and is more pure. In an SR system, the input signal frequency is limited to far less than 1 Hz due to its adiabatic approximation condition [43]. However, in practical engineering application, the bearing has a fault characteristic frequency that is far more than 1 Hz. Lu et al. [44] proposed a standardized scale conversion non-stress test (NST) SR. Leng et al. [45] presented a variable scale SR method to satisfy the small parameter condition of SR, which compresses large frequency signals to small frequency signals (frequency less than 1 Hz) according to a certain scale. Tan et al. [46] studied a method of frequency-shifted and re-scaling SR (FRSR) to achieve small parameter conditions. Large frequency signals are first processed by a high-pass filter, and then combined with frequency-shifted and re-scaling technology. The above two methods play an important role in practical engineering application. In addressing the problem of system parameters selection, Zhang et al. [47] found that the selection of classical SR (CSR) system parameters can be achieved under the condition of particle swarm optimization (PSO), which can be easily interfered with by low-frequency information. Lei et al. [48] introduced a method of ant colony optimization algorithm to analyze the signal after FRSR to determine the system parameters, but the operation of this method with the help of a high-pass filter is complex. Lu et al. [49] analyzed the underdamped step-varying second-order SR (USSSR) method. Compared with the first-order SR system, the second-order filtering performance is better, and the dependence on the filter is eliminated. Luo [50] gave specific steps to solve the USSSR parameters by ant colony optimization algorithm. Lei et al. [51] further analyzed the advantages of a second-order multistable SR system. However, the coupling model studies the SR system from another point of view. There is little research on the SR coupling model. Zhang et al. [52] studied the coupling bistable system and used it for fault signal detection. Li et al. [53] further studied a novel adaptive SR method based on coupled bistable systems and its application in rolling bearing fault diagnosis. Although the output of SNR has been improved, its effect is not good.

Based on the above analysis, we proposed a second-order coupled step-varying stochastic resonance (SCSSR) model, which is a further evolution of the coupled SR model. Compared with the existing first-order SR, second-order tristable SR, and coupled stochastic resonance systems, there are not many studies on second-order coupled SR systems. We used the seeker optimization algorithm (SOA) to determine the model parameters with the output SNR as its fitness function. This article provides the steps and processes to select system parameters based on SOA. The results of simulation and engineering data show that the system can enhance and extract the weak characteristic signals and that the system has better performance in weak signal extraction and filtering; the output SNR is also higher than that of traditional SR systems.

2. Fundamental Theory

2.1. Second-Order Coupled Stochastic Resonance System Model

The SCSSR model composed of two second-order bistable SR system models is as follows:

In the above formula:

$$V_1(x) = -\frac{1}{2}a_0x^2 + \frac{1}{4}b_0x^4$$

$$V_2(y) = -\frac{1}{2}ay^2 + \frac{1}{4}by^4$$
(2)

where *r* is the coupling coefficient, *k* is the damping coefficient, and a_0 and b_0 are fixed values. In this paper, $a_0 = 1$, $b_0 = 1$, *a* and *b* are parameter variables, and the input signal is s(t) + n(t). The coupled bistable system consists of control system *y* and controlled system *x*; x(t) and y(t) are the output variables of two second-order SR systems. Because the noise and signal act on the controlled system,

x(t) is the final output for the coupled SR system. Formula (1) can be solved with the fourth-order Runge–Kutta equation [54].

When r = 0, it can be seen from Formula (1) that the coupled SR system is two independent second-order SR systems, its output is still x(t), and the final SR system is changed to an USSSR system.

When the coupling system interacts with the signal and noise to produce an SR phenomenon, it can be expressed as the following equation:

$$U(x,y) = -\frac{1}{2}a_0x^2 + \frac{1}{4}b_0x^4 - \frac{1}{2}ay^2 + \frac{1}{4}by^4 - \frac{r}{2}(y^2 - x^2)$$
(3)

Take $a_0 = 1$, $b_0 = 1$, a = 1, b = 1, r = -0.06; Figure 1 shows the coupling system potential function U(x, y). This potential well function is more complex and comprehensive than the traditional bistable potential well function, the dynamic performance of the potential function is better, the particle motion is accelerated, and the SR state is better.



Figure 1. The potential function of U(x, y).

2.2. Measure Index

The SNR is often used as a measure of the SR model, however, in this paper the output SNR is different from the traditional output SNR [55]. The specific calculation of the output SNR is as follows:

For a group of discrete signals $x = \{x_1, x_2, \dots, x_N\}$ (*N* means the signal length), in the frequency domain, we can acquire *X*(*k*) by FFT and amplitude sequence *Y*(*k*) by the following expression:

$$X(k) = \sum_{n=1}^{N} x(n) e^{-j\pi(k-1)(n-1)/N}, 1 \le k \le N$$

$$Y(k) = 2\frac{|X(k)|}{N}, 1 \le \frac{N}{2}$$
(4)

Let the peak number of the spectrum at the signal frequency f_0 be K_0 , which can be gained from the following formula:

$$K_0 = \frac{f_0 \times N}{f_s} + 1 \tag{5}$$

The sampling frequency of the signal is f_s , from which the output SNR can be expressed below:

$$SNR = 10 \log \frac{Y(K_0)}{\sum_{K=1}^{\frac{N}{2}} Y(K) - Y(K_0)}$$
(6)

2.3. SCSSR Algorithm Flow

Based on the small parameter condition of the input of the SR system, the frequency compression ratio (R) is introduced here to make the actual vibration large frequency signal meet it. For the selection of system parameters, this paper uses SOA [56,57] to optimize the parameters a, b, r, k, and R synchronously, with the output SNR as its fitness function. Figure 2 shows the system flow chart.



Figure 2. Flowchart of stochastic resonance (SR) based on the seeker optimization algorithm (SOA).

The specific implementation steps are given below:

- Signal preprocessing: The obtained vibration signal is preprocessed; The resonance band of the vibration signal is found through power spectrum analysis; And band-pass filtering and Hilbert transform (HT) are carried out; Finally we can get the envelope signal S_1 , $S_2 = S_1 mean(S_1)$, $S_3 = max(abs(S_2))$, and $S_4 = S_2/(2 * (S_3))$; S_4 is the input signal. The above operations ensure that S_4 is the signal with amplitude less than 1.
- System parameters initialization: Determine the maximum number of iterations and population size of SOA. Set the optimization range of five parameters.
- Take the output SNR as the fitness function of SOA.
- Record the number of iterations. If it reaches the maximum number of iterations, proceed to the next step; if it does not, return to the previous step.
- Record the maximum output SNR and get the values of the five parameters at this time.
- Weak signal detection: The preprocessed signal is introduced into the determined parameter SCSSR system to get the output. Recombine the frequency and amplitude to complete the detection of a weak signal.

3. Simulation Data Analysis

In order to obtain a simulated sine signal with a low SNR, the periodicity and characteristic frequency of the signal cannot be seen in the time-domain waveform and amplitude spectrum.

Set $s(t) = A_0 \sin(2\pi f_0 t) + n(t)$ as the input of the SCSSR system, where n(t) is Gaussian white noise, $A_0 = 0.2$, $f_0 = 50$ Hz, the intensity is 2.4, the sampling number is 5000, and the sampling frequency and frequency resolution are 5 kHz and 1 Hz, respectively. Figure 3a shows the time-domain waveform and amplitude spectrum of signal. It is hard to discover the frequency component of 50 Hz from the amplitude spectrum; the SNR of the input signal obtained from Formula (6) is -29.82 dB, which is very low.



Figure 3. Cont.



Figure 3. Analysis results for the simulation signal: (**a**) original signal; (**b**) classical system parameters (CSR) output signal; (**c**) underdamped step-varying second-order (USSSR) output signal; (**d**) second-order coupled step-varying stochastic resonance (SCSSR) output signal; (**e**) SCSSR output signal when a is changed.

The output result of data processed by the CSR system is shown in Figure 3b. Simultaneously, R = 464, a = 19.7, b = 7217.3, and SNR is -20.53 dB. Although the high frequency components are suppressed, the SNR is improved, but at the same time of the scale transformation of the low frequency components, which also enhances the noise energy. The output result of data processed by the USSSR system is shown in Figure 3c. From the figure, we find that the amplitude of characteristic frequency is significantly increased. The system parameters are shown below: a = 2.343, b = 10431.666, k = 0.13, r = 131.44, and the output SNR = -11.49 dB. The simulation signal shows that when contrasted with the first-order SR system, the second-order SR system has better filtering characteristics. We inputted the signal to the SCSSR and the optimal parameters are gained: a = -5.5, b = 12.43, k = 0.54, r = 2.85, R = 147.2, and the output SNR is -2.684 dB. By observing Figure 3d, for this signal we find that the time-domain waveform shows its periodicity, the frequency component of 50 Hz is also clearly reflected in the amplitude spectrum, and there are almost no other frequencies. This fully demonstrates the reliability of the SCSSR method. To analyze the effect of the selected parameters on the results, we changed the parameters obtained by the SCSSR method and changed a = -5.5 to a = -100. The results are shown in Figure 3e. As can be seen from the Figure 3d,e, the system parameters greatly influence the results.

4. Engineering Applications

By analyzing the bearing experimental data of Case Western Reserve University [58], we further confirmed the feasibility of the SCSSR method. The experiment uses a deep groove ball bearing, whose type is 6205-2RS JEM SKF (SKY FU (SHANGHAI) RESPONSIBILITY LIMITED, Shanghai, China). Table 1 shows the dimensional parameters of the bearing. In comparison, since the FRSR needs to set the filter, the operation is cumbersome. This paper only analyzes the data with CSR and USSSR.

Inner Diameter	Outer Ring Diameter	Number of Rollers	Rolling Element Diameter	Pitch Distance
2.5001 cm	5.1999 cm	9	0.794 cm	3.904 cm

Table 1. Size parameters of 6205-2RS.

The acceleration sensor is used to gather a vibration signal; the sampling number is 4096, the sampling frequency is 12 kHz, and 1730 r/min is the motor speed. The inner ring theory fault characteristic frequency is 156.14 Hz. The time-domain waveform and power spectrum of the bearing inner ring fault signal collected by the experiment are shown in Figure 4a. We are not able to discover the periodic component in the time-domain waveform, and from the power spectrum, we are not able to observe the inner ring fault characteristic frequency f_{BPFI} . By bandpass-filtering the original signal, the filtered signal is subjected to the HT transform to acquire an envelope signal and an envelope

amplitude spectrum, as displayed in Figure 4b. We can see the inner ring fault characteristic frequency f_{BPFI} , from the envelope amplitude spectrum, but it is difficult to judge the fault due to the interference of the surrounding noise and the frequency conversion f_r . The SNR is -17.53 dB from Equation (6). Figure 4c is the result of using the CSR system to process the envelope signal. In this figure, the energy of high frequency is lower, and the feature of the inner ring fault frequency f_{BPFI} and the frequency conversion f_r is amplified. The system parameters are shown below: *a* is 0.0015; *b* is 5235.68; *R* is 672.536; the output SNR is -15.511 dB. After the data are processed by the USSSR system, the system parameters are a = 0.908, b = 12476.8, R = 304.395, k = 0.222; the output results are shown in Figure 4d, the SNR is reduced to -10.42 dB, and f_{BPFI} can be clearly found in the amplitude spectrum. Meanwhile, the output SNR comparison CSR system is further enhanced. If the SCSSR algorithm is used to process the envelope, the outputs are shown in Figure 4e. The optimal parameters are a = 4.5, b = 1.6, k = 0.9, r = -4.3, R = 556.51, and the output SNR is -2.636 dB. The output signal of the *y* channel effectively enhances the *x* channel output, and the frequency f_{BPFI} is clearly visible. Once again, the bearing fault data analysis results demonstrate the feasibility and superiority of the SCSSR method.



Figure 4. Cont.



Figure 4. Analysis results for the bearing signals with inner race: (**a**) original signal; (**b**) envelope signal; (**c**) CSR output signal; (**d**) USSSR output signal; (**e**) SCSSR output signal.

5. Conclusions

The SCSSR system proposed in this paper can enhance and extract bearing fault characteristics under a strong noise background. The main conclusions are as follows:

- 1. For large-parameter signals, combined with the variable-scale method, the SCSSR system can detect weak signals.
- 2. SOA is used to determine model parameters of the SCSSR system with the output SNR as its fitness function.
- 3. Simulation and engineering data show that the SCSSR has better filtering performance and higher output SNR than the traditional SR method.

Although this article makes the characteristic frequency of the useful signal obvious, it still relies on the output SNR as a measure of SR. Future work should focus on how to identify the detection of unknown characteristic frequency signals.

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