Application of Human Cognitive Self Regulating Particle Swarm Optimization and Stochastic Resonance in Bearing Fault Diagnosis

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Abstract: This paper presents a bearing fault diagnosis algorithm based on human self regulating particle swarm optimization and stochastic resonance. The algorithm first sets up the objective function according to the stochastic resonance structural parameters a and b. Then the self regulating particle swarm optimization algorithm is used to optimize the objective function, and the optimized optimal values a and b are substituted into the system of variable scale stochastic resonance. Finally, the measured bearing vibration signal to noise reduction and spectrum analysis to find the bearing fault characteristic frequency. Experimental results show that this method is effective in bearing fault diagnosis.

Introduction

For the essence of fault diagnosis of rotating machinery, that is the process of feature extraction and pattern recognition of vibration signals, the feature extraction of fault signals is still a difficult problem in current fault diagnosis, [1] how to extract features and how to identify faults based on signal faults And how to pattern recognition, these issues become the core of signal processing. For the measured vibration fault signal is often non-stationary and non-linear, and the traditional signal processing methods in practical application of the effect is often not very satisfactory.[2]Such as fast Fourier transform (FFT), Wigner-Ville, traditional wavelet transform, etc., the above methods usually can not accurately reflect the essential characteristics of the signal.

In 1995, Particle Swarm Optimization (PSO) algorithm was proposed by Kennead et al. [3] This algorithm is a kind of adaptive evolutionary computation based on population search, which has the advantages of easy implementation, less parameters, and can effectively solve complex optimization tasks.[4] Therefore, it has been widely researched by scholars. With the rapid development of science and technology, PSO has been widely used in image processing, pattern recognition and optimization.

As a new random search algorithm, PSO algorithm has some problems such as falling into a local extreme point, slow convergence and poor accuracy in the late evolutionary stage. In response to the above problems, the researchers from all aspects of the PSO algorithm has been improved, a large number of research results have been obtained. Literature [5] proposed adaptive escape particle swarm optimization algorithm, which changed particle's flight speed in search space through the adaptive change of velocity. The results show that the convergence speed of PSO algorithm is improved to a certain extent.

Literature [6] proposed the Self Regulating Particle Swarm Optimization (SRPSO) algorithm, which is based on the basic PSO algorithm to develop self-regulation and self-awareness of the PSO algorithm. According to human cognitive psychology, the best decision-makers can self-regulate and self-cognize global knowledge according to the current situation. Self-regulation and collaborative learning can help human beings make better decisions based on their current state and expectations.

Stochastic Resonance (SR) was proposed by Benzi [7] et al. In 1981 when studying paleoclimate glaciers. However, due to the small parameters, that is, the system input signal s(t) frequency, amplitude, noise intensity is far less than 1, and engineering practice, the signal is often a large
parameter signal does not meet the conditions of small parameters. In view of the problem that stochastic resonance can not handle large parameter signals, Leng Y G [8] proposed a variable-size stochastic resonance method. By setting a suitable compression ratio R, the sampling frequency of large parameters is transformed and compressed, Used under parameter conditions. However, the structural parameters a and b of the system are usually fixed at 1, which are not self-adaptive.

In order to visualize the faint impact signal in the fault signal, stochastic resonance is applied to the extraction of weak fault signature signals by most scholars. The difference with the traditional noise reduction method is that stochastic resonance is the use of noise energy to enhance the bearing fault weak component. Literature [9] proposed an adaptive stochastic resonance method, and used the signal to noise ratio as the performance index to evaluate the output signal of stochastic resonance system.

In view of this, this paper presents a stochastic resonance method of SRPSO. Firstly, the objective function is defined as the signal output signal-to-noise ratio. Then SRPSO is used to optimize the stochastic resonance structural parameters a and b. Finally, the parameters a, b corresponding to the fitness value maximizing the signal to noise ratio are brought into a scale-scale stochastic resonance, and the input fault signal is de-noised, the time-frequency diagram is obtained, and the fault characteristic frequency of the bearing is looked for in the frequency spectrum.

**SRPSO Theory**

Inspired by the principle of human learning in human cognitive psychology, M.R. Tanweer et al [6]. Proposed a self-regulating learning algorithm, Experimental results show that the algorithm has better generalization performance and self-regulation and collaborative learning ability than other algorithms, which can help people to make better decisions based on the current state and expected goals. The specific algorithm is as follows:

SRPSO has been improved on the basis of PSO algorithm, the speed update equation in SRPSO is as follows:

\[
V_{id}^{t+1} = w_{id}V_{id}^t + c_1r_1p_{id}^\text{so}(P_{id}^t - X_{id}^t) + c_2r_2p_{id}^\text{gd}(P_{id}^t - X_{id}^t)
\]  

Where \( V_{id} \) and \( X_{id} \) are the velocity and position of the ith particle in the d-dimensional space, respectively. \( t \) and \( t_1 \) represent the current and next iterations, respectively, representing the optimal position of the i-th particle in the d-dimensional space, which represents the optimal position found by all the particles in the d-dimensional space. \( c_1 \) and \( c_2 \) represent the acceleration coefficients, and \( r_1 \) and \( r_2 \) represent random numbers distributed uniformly in the interval \([0,1]\). \( w_i \) denotes the inertia weight of the ith particle, which is self-regulated by the optimal particle.

\( p_{id}^\text{so} \) is the particle's self-awareness of the individual, \( p_{id}^\text{gd} \) is the particle’s global perception, they are defined as follows:

\[
p_{id}^\text{so} = \begin{cases} 0, \text{optimal particles} \\ 1, \text{other particles} \end{cases}, \quad p_{id}^\text{gd} = \begin{cases} 0, \text{optimal particles} \\ \gamma, \text{other particles} \end{cases}
\]

\( \gamma \) is binary \((0, 1)\), the value depends on the definition of the threshold of confidence. The self-adjusting inertia weight strategy is defined as follows:

\[
w_i = \begin{cases} w_i(t) + \eta \Delta w, & \text{Optimal particles} \\ w_i(t) + \Delta w, & \text{Other particles} \end{cases}
\]

Where: \( w_i \) is the current inertia weight, and

\[
\Delta w = \frac{w_i - w_F}{N_{\text{iter}}} = 0.55 \frac{N_{\text{iter}}}{N_{\text{iter}}}
\]

\( N_{\text{iter}} \) is the number of iterations, and \( w_i \) and \( w_F \) are the initial and final inertia weights. \( \eta \) is a constant that controls the rate of acceleration, usually set to 1. \( \alpha \) obeys the uniform distribution on \([0,1]\), which is the direction of all global optimal positions. Threshold \((\lambda)\) is set to 0.5 to achieve any choice of direction, the social awareness of particles as follows:
\[ P_{id}^w = \begin{cases} 1 & \text{if } a > \lambda \\ 0 & \text{otherwise} \end{cases} \quad i = 1, 2, \ldots, m \]  

(4)

Self-awareness apparently affects the search direction of the particle, but for the optimal particle, it is the best orientation and discards the social and self-perception. Therefore, the velocity update equation of the optimal particle is as follows:

\[ V_{id}^{\text{opt}} = w_i V_{id} \]  

(5)

Other particles:

\[ V_{id}^{\text{opt}} = w_i V_{id} + c_1 r_i (P_{id}^i - X_{id}^i) + c_2 r_i P_{id}^w (P_{id}^w - X_{id}^w) \]  

(6)

**Stochastic Resonance (SR) Theory**

In the study of stochastic resonance, the expression of potential function is:

\[ U(x) = -\frac{1}{2} ax^2 + \frac{1}{4} bx^4 \]  

(7)

Where, \( a \) and \( b \) are the structural parameters of the bistable system. The deterministic dynamic system equation for one-dimensional nonlinear bistable systems without considering noise is:

\[ \frac{dx}{dt} = ax - bx^3 + \sin(2\pi f_0 t) \]  

(8)

Where \( n(t) \) is Gaussian white noise (mean 0, noise intensity \( D \)). When choosing \( a, b \) and \( D \) in the bistable system properly, the output response of the system will satisfy the stochastic resonance condition, that is, the jumping frequency of the particles between the two potential wells reaches the signal frequency and enhances the weak periodic signal.

For the random noise reduction effect is not obvious and can only detect the small parameters of the signal (adiabatic approximation small parameter conditions \( A \ll 1, D \ll 1, f_0 \ll 1 \)) The basic idea is as follows:

1. set a frequency compression ratio \( R \);
2. Define a compressed sampling frequency \( f_{sr} = f_s / R \);
3. Set the Runge-Kutta method to calculate the step size \( h = 1 / f_{sr} \).

The large parameters of the actual signal sampling frequency through R-switched bistable stochastic resonance processing, you can get small parameters under the conditions of the system output response.
Adaptive Stochastic Resonance Method

When the traditional adaptive optimization method is used to optimize the structural parameters in stochastic resonance, there are some limitations, such as being fixed and optimizing only b. Thus ignoring the mutual synergy between a and b, resulting in the algorithm is limited in engineering applications. Therefore, this paper proposes an algorithm of human cognitive self-adjusting particle swarm optimization to optimize the structural parameters a and b of stochastic resonance, aiming to make the selection of a and b adaptive.

The proposed method takes the output signal-to-noise ratio of the system as the objective optimization function to maximize the signal-to-noise ratio of the output signal and optimize the output parameter values \( a \) and \( b \). Then the optimal values \( a, b \) are brought into the bistable stochastic resonance system for Runge-Kutta calculation. Finally, the optimal stochastic resonance is used to de-noising the measured vibration signals and to obtain the time-frequency spectrum, and the characteristic frequency of the bearing fault is found in the spectrogram. The specific steps of the algorithm proposed in this paper are as follows:

1. Initialization: Set the population size, randomly select individuals to form an initial population.
2. Set the objective function: the objective function of the genetic algorithm is defined as the output signal to noise ratio of the system \( F(a, b) = SNR_{out}(sr(a, b)) \), Where \( sr(a, b) \) is the output of a variable-scale bistable stochastic resonance and \( SNR_{out}(sr(a, b)) \) is the signal-to-noise ratio of the system output.

Then the corresponding parameters of each individual are brought into the bistable stochastic resonance system. The fourth order Runge-Kutta algorithm is used to calculate the output signal and its power spectrum. Finally, individual fitness values are calculated according to the signal frequency and power spectrum.
3. Stochastic Resonance Denoising: The parameters \( a \) and \( b \) corresponding to the fitness value maximizing the signal-to-noise ratio are brought into the bistable stochastic resonance with variable scales to perform noise elimination on the input fault signal.
4. Time-frequency spectrum: The time-frequency spectrum of the fault signal after stochastic resonance de-noising.
5. Make a decision: Calculate the fault frequency according to the bearing parameters to determine the fault type of the bearing.

Signal Simulation

Set the simulation signal is: \( x_1(t) = 0.6 \sin(2\pi 30t) + n(t), n(t) = \sqrt{2D}g(t) \), The white noise intensity D is 9.1, the mean is 0, the variance is 1, the sampling frequency \( f_s \) is 2000 Hz, the sampling point number N is 2000, and the time-frequency spectrum of the simulation signal is shown in Fig. 2.

![Figure 2. Simulation signal time-domain diagram.](image)

In accordance with the traditional random resonance simulation signal denoising (a = 1, b = 1), the signal output results shown in Figure 3:
After SRPSO-optimized SR output signal results shown in Fig4. It can be seen from the time-frequency spectrum that the noise reduction effect of the signal is improved to some extent, and the amplitude of the characteristic frequency of the simulation signal is more obvious with respect to Fig.3.

**Experimental Analysis**

Experimental data from the Case Western Reserve University, will support the motor-driven 6205-2RS deep groove ball bearings as a test bearing, the use of bearing inner ring signal analysis. A single point of failure was placed on the bearing using EDM with a diameter of 0.007 inch (1 inch =25.4 mm) diameter and the bearings used were SKF bearings. The number of balls is 9, after calculation, the diameter of the rolling element is 7.94mm and the bearing pitch is 39.04mm. According to the bearing parameters, the fault characteristic frequency of the bearing inner ring is 157.94Hz.

Experiment, the motor speed of 1750 r/min sampling frequency of 12kHz, rolling bearing experimental platform components include a 2 horsepower motor, a torque sensor, a power meter and electronic control equipment. Rolling bearing test bench shown in Figure 5.
Bearing Inner Ring Failure Analysis

Artificial selection 4800 data points under the inner circle fault analysis. Inner ring fault bearing signal time domain waveform shown in Figure 6.

![Figure 6. Inner ring bearing fault signal waveform.](image)

Traditional random resonance (a=1, b=1) results of noise cancellation shown in Figure 7:

![Figure 7. Traditional random noise reduction results.](image)

Figure 8 shows the results of de-noising bearing signals after SRPSO-optimized stochastic resonance. The optimal parameters a = 0.0008 and b = 0.001. It can be seen from the frequency domain in the figure that relative to Fig.7, the bearing fault characteristic frequency is more obvious and the amplitude is larger.
Conclusion

This paper studies a fault diagnosis method based on human cognitive self-tuning particle swarm optimization and stochastic resonance algorithm. Concluded as follows:

1. SRPSO overcomes artificially selected random resonance parameters a and b.
2. Scaled bistable stochastic resonance algorithm based on SRPSO optimization compared with the traditional stochastic resonance algorithm, denoising effect is better.

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Reference


