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Weak Fault Diagnosis of Rolling Bearing Based on Improved Stochastic Resonance

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Abstract: Stochastic resonance can use noise to enhance weak signals, effectively reducing the effect of noise signals on feature extraction. In order to improve the early fault recognition rate of rolling bearings, and to overcome the shortcomings of lack of interaction in the selection of SR (Stochastic Resonance) method parameters and the lack of validation of the extracted features, an adaptive genetic random resonance early fault diagnosis method for rolling bearings was proposed. compared with the existing methods, the AGSR (Adaptive Genetic Stochastic Resonance) method uses genetic algorithms to optimize the system parameters, and further optimizes the parameters while considering the interaction between the parameters. This method can effectively extract the weak fault features of the bearing. In order to verify the effect of feature extraction, the feature signal extracted by AGSR method was input into the Fully connected neural network for fault diagnosis. the practicality of the algorithm is verified by simulation data and rolling bearing experimental data. the results show that the proposed method can effectively detect the early weak features of rolling bearings, and the fault diagnosis effect is better than the existing methods.

Keywords: Rolling bearing, weak fault, stochastic resonance, genetic algorithm, neural network.

1 Introduction

With the rapid development of industrial mechanization, the power and efficiency of mechanical equipment have also been continuously improved, and the working status of equipment has also become complicated and changeable, which has caused many difficulties in fault diagnosis. Rolling bearings are widely used in machinery industry and other fields due to their advantages of strong bearing capacity and small friction coefficient, and they are also one of the most easily damaged components in rotating machinery.

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However, the features of early bearing fault signals are weak and susceptible to noise and human interference. If bearing failures can be diagnosed and repaired as soon as possible, safety hazards and economic losses can be effectively reduced. Therefore, early weak feature extraction has always been one of the research hotspots in mechanical fault diagnosis. Traditional weak signal detection methods mostly suppress and eliminate noise to improve signal-to-noise ratio, such as empirical mode decomposition [Lei (2001)], Wavelet transform [Wang, Tao and Zhang (2017); Purushotham, Narayanan and Prasad (2005)], and so on. Hu et al. [Hu, Ma and Tang (2012)]. Used the integrated empirical mode decomposition and kurtosis criterion to extract the fault feature information of rolling bearings, and effectively suppressed the mod-al aliasing problem during the empirical mode decomposition. It also avoids the errors caused by improper selection of the frequency and filter band of the resonance de-modulation method. Pan et al. [Pan, Liang, Li et al. (2015)] proposed a bearing fault feature extraction method based on Complex wavelet multiscale envelope analysis, which overcomes the shortcomings of classical envelope analysis methods that need to predict the fault frequency band.

Although the above method exhibits good features in fault diagnosis, the feature signal that is unavoidably weakened while reducing noise will affect the diagnosing effect of a weak fault. The Stochastic Resonance (SR) theory is proposed by the Italian scholar Benzi et al. [Benzi, Sutera and Vulpiana (1981)]. Compared with the traditional method, SR can transfer the energy of some noise signals to the weak feature signals, and reduce the noise while enhancing the feature of weak signals. It can realize the early weak signal detection in the noise background.

Due to the limitation of adiabatic approximation theory [Li, Chen and He (2013)], when the driving signal frequency is gradually increased, the peaks of the driving signal will be far away from the low-frequency region where the noise energy is concentrated, so that the noise energy cannot support the particles when they jump between the potential wells, and eventually the noise energy cannot be transferred to the signal through the random resonance. SR theory can usually only detect signals with lower frequencies, which seriously affects the popularity of SR methods in industrial applications.

In recent years, some scholars have improved the stochastic resonance method, Chen et al. [Chen, Hu, Qin et al. (2009)] proposed using signal-to-noise ratio gain as a measure of signal enhancement by the SR method, and proposed a new weak signal detection method with adaptive parameter adjustment. Tan et al. [Tan, Chen, Lei et al. (2009)] used two kinds of trans-formation of frequency shift and variable metric method for signal preprocessing, and combined with stochastic resonance to detect high-frequency signals. However, the existing SR method only optimizes a single parameter and ignores the interaction between the parameters, failing to fully exploit the ability of the stochastic resonance method to extract weak signals. In addition, weak fault signals extracted by stochastic resonances are also lacking validation in actual engineering diagnostics.

Based on this analysis, a new method of adaptive stochastic resonance (AGSR) based on genetic algorithm (GA) was proposed. In this paper, the genetic algorithm is used to select and optimize multiple parameters of the stochastic resonance system in parallel, adaptively achieving the best match with the input signal and overcoming the disadvantages of the existing method parameter selection. Then, the pre-processed bearing signals are classified using a fully connected neural network achieve fault diagnosis. In order to verify the experimental results, Western Reserve University bearing vibration failure data was used as a research object, the fault diagnosis performance of the extracted feature [Zhao, Wu, Zhang et al. (2018); Wang, Zhao, Wu et al. (2017)] of the AGSR method is verified, and the effectiveness and practicability of the AGSR method are proved.

This paper is organized as follows: SR and AGSR methods are introduced in Section 2. In Section 3, a description of data preprocessing and model design is provided. In Section 4, the actual effects of the SR and AGSR preprocessing on the classification of weak faults are compared through experiments. The specific performance of AGSR on the time and frequency domain signals is given in detail. In Section 5, the paper is concluded.

2 Signal preprocessing based on stochastic resonance

2.1 Stochastic resonance theory

Stochastic resonance systems are usually composed of three elements: non-linear bistable systems, input signals and noise. The system output can be described by Langevin equation:

$$\dot{x} = -U(x) + \mathrm{s}(t) + n(t) \tag{1}$$

$U(x)$ is nonlinear bistable system. $\mathrm{s}(t)$ is Periodic signal. $n(t)$ is Zero-mean Gaussian white noise. The potential function of the bistable system is:

$$U(x) = -\frac{a}{2}x^2 + \frac{b}{4}x^4 \tag{2}$$

where *a* and *b* are the structural parameters of the bistable system, satisfying $a>0$, $b>0$.

This paper uses the fourth-order Runge-Kutta to solve the Langevin equation in (1). The equation is as follows:

$$\begin{cases} k_1 = h(ax_n - bx_n^3 + s_n) \\ k_2 = h[a(x_i + \frac{k_1}{2}) - b(x_i + \frac{k_1}{2})^3 + s_i] \\ k_3 = h[a(x_i + \frac{k_2}{2}) - b(x_i + \frac{k_2}{2})^3 + s_{i+1}] \\ k_4 = h[a(x_i + k_3) - b(x_i + k_3)^3 + s_{i+1}] \\ x_{i+1} = x_i + \frac{1}{6}(k_1 + 2k_2 + 2k_3 + k_4) \end{cases} \tag{3}$$

n is the input signal length.

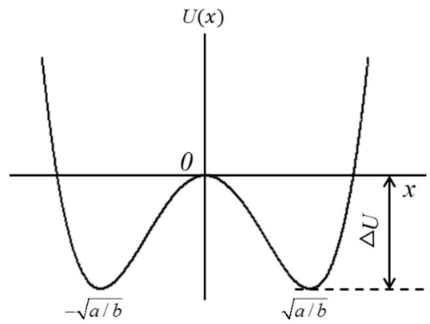


Figure 1: Potential well of bistable function

As shown in Fig. 1, the potential traps on both sides of the bistable system represent its two steady states $x=\pm\sqrt{a/b}$ .The height of the barrier is. $\Delta U(x)=a^2/4b$. When the signal is input, the system is blocked by the barrier wall ΔU and can only perform periodic motion in a potential well.

At this point, noise is added to the system. Under the combined action of the input signal and noise, the system moves through the barrier wall and makes a transition between the two steady states. this is the phenomenon of stochastic resonance.

Noise motivates the transition movement. When the three-state system, signal and noise reach the best matching state, the effect of stochastic resonance on signal amplification [Mendezbalbuena, Manjarrez, Schultemönting et al. (2012)] is also most obvious.

2.2 Adaptive genetic stochastic resonance

The barrier height ΔU in the stochastic resonance system is the main factor that limits the signal transition. ΔU too high stochastic resonance is difficult to generate, ΔU too low will make the random resonance effect not obvious, and the system parameters a and b determine the barrier height $\Delta U(x)=a^2/4b$. Therefore, this paper proposes to optimize the system parameters by genetic algorithm. Limited by the adiabatic approximation theory, the SR theory only applies to low-frequency signals, and the bearing signal frequency far exceeds this range.

In order to improve the applicable range of stochastic resonance theory, the scale transformation stochastic resonance [Leng, Wang and Li (2003)] method is used to process the fault signal under large-parameter conditions. By defining the frequency compression ratio R, the signal is sub-sampled to satisfy the low frequency condition, and then the feature of weak signal is enhanced by the SR method.

The AGSR method uses genetic algorithm to optimize the system parameters a and b. The signal-to-noise ratio (SNR) after stochastic resonance is used as the fitness function of the genetic algorithm. The stochastic resonance steps of the genetic algorithm are briefly described as follows:

1) Population parameter initialization. Set the population size G, the chromosome length L, and the evolution number K, and use the binary coding method to map the range of values for variables a∈$[a_{\min}, a_{\max}]$ and b∈$[b_{\min}, b_{\max}]$.

2) Calculation of fitness of parents' population. The decoded a and b values of the parental individual are assigned to the stochastic resonance system, and the output signal after the stochastic resonance of the compressed signal is calculated, and the signal to SNR of the output signal is taken as a fitness function. The SNR is calculated as follows:

$$SNR = 10\lg(\mathrm{S/N}) \tag{4}$$

where S is the signal energy and N is the noise energy. When the parameters of the stochastic resonance system are optimal, the signal-to-noise ratio is maximized.

3) Screening offspring individuals. Using roulette selection method to select parents, the greater the probability that individuals with higher fitness are selected. Then select the individual to do crossover and mutation operations to obtain offspring individuals.

4) Finding optimized populations. Take the offspring individuals as the parent of the next generation and repeat Steps (2) through (3) until the fitness function converges or reaches the maximum number of iterations to obtain the optimal parameters a_k and b_k .

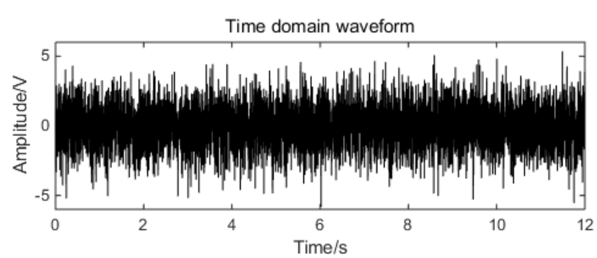
5) Substituting the optimal parameters a_k and b_k into a stochastic resonance system to realize the enhancement and extraction of early weak signal of rolling bearing.

2.3 Simulation signal analysis

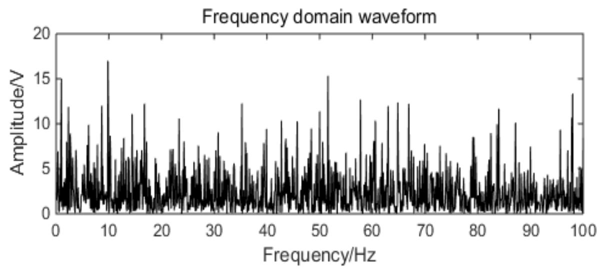
The SR method can effectively extract low-frequency signals. In actual industrial production, the signals often exceed the limitations of the SR method. In order to prove the shortcomings of the SR method, we also test the effectiveness of the AGSR method. the simulated high-frequency input signal is

$$S(t) = 0.1 \times \cos(2\pi \times 50 \times t) \tag{5}$$

The sampling frequency is 500 Hz, the number of sampling points is 6000, and adding zero mean Gaussian white noise with noise intensity D=1.2. The time domain waveform and frequency domain waveform of the simulated signal are shown in Fig. 2.



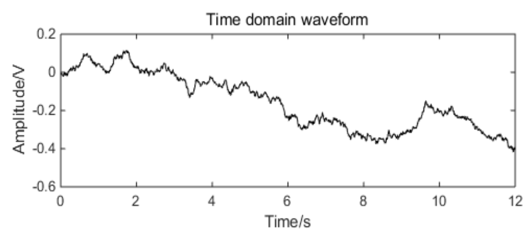
(a)



(b)

Figure 2: Simulated simulation signal

As can be seen from Fig. 2, the feature frequency of 50 Hz affected by the background noise has been submerged by noise, and it is difficult to clearly identify from the spectrum diagram. The output of the SR system is analyzed and the results are shown in Fig. 3. It can be seen that the output time domain waveform can no longer see obvious periodic fluctuations; while the spectrum signal shows a monotonous decreasing trend and does not show any spectral peak features. this shows that when the SR method processes high frequency signals, it will deviate greatly due to adiabatic approximation theory. Therefore, it is not appropriate to directly use the SR method to process high-frequency signals.



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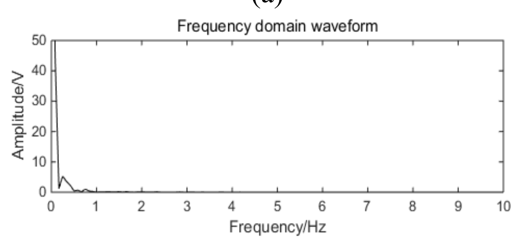
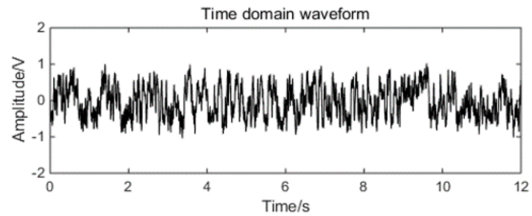


(b)

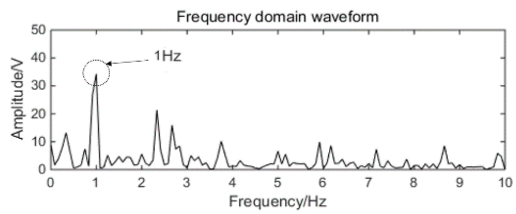
Figure 3: SR output time frequency diagram

The simulated signal is analyzed using the AGSR. First, set the frequency compression ratio to R=50 and linearly compress the signal. then use the genetic algorithm to find the optimal combination of variables a and b in the range [0, 10]. After 50 iterations, the optimization result is a=0.31, b=2.73, SNR=-2.306.

As can be seen from Fig. 4(b), 1Hz frequency is very prominent in the spectrum diagram, because the signal is pre-processed using the variable-scale method, the corresponding frequency is 50 Hz, which is the original signal's feature frequency. Therefore, the AGSR can detect weak signals in strong noise background, and overcome the shortcomings of traditional stochastic resonance methods that can only extract low frequency signals.



(a)



(b)

Figure 4: AGSR output time frequency diagram

3 Bearing fault diagnosis based on AGSR pretreatment

The early failure signal of the rolling bearing has the features of complexity, non-stationarity and similarity between different fault signals. Therefore, this paper proposes the use of the fully connected neural network for fault diagnosis of pre-processed bearing signals [Hinton, Osindero and THE (2006); Lei, Jia and Zhou (2015); Gan, Wang and Zhu (2016)]. In order to meet the needs of rolling bearing fault diagnosis, a five-layer neural network structure is adopted. The last layer is a Softmax classifier. the network is trained by inputting the signal X. Fully connected neural network trains network layer by layer through the gradient descent method, so that the output low-dimensional signal includes the fault essence features while removing the interference part of the high-dimensional signal.

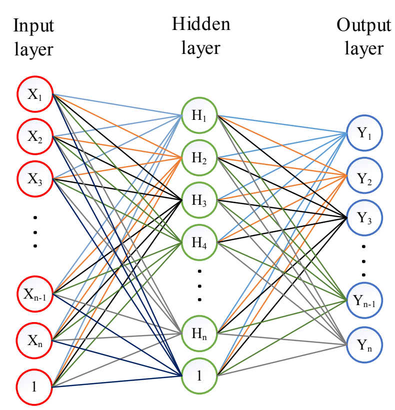


Figure 5: Fully connected neural network structure

Then, the extracted feature signals are used in the classification of Softmax classifiers. According to the classification results, the original signal labels are used to fine-tune and optimize the network and finally used for fault diagnosis of rolling bearings. In summary, fully connected neural network can extract the feature factors of high-dimensional data, enhance the robustness of the algorithm, and improve the linear separability of features to achieve accurate fault diagnosis.

Fig. 6 shows the bearing fault diagnosis based on improved stochastic resonance preprocessing. The specific steps are as follows:

Step 1: Set the input signal to s(t), and use the variable-scale method to preprocess the input signal.

Step 2: Initialize the parameters of the genetic algorithm and select SNR as the evaluation function of the improved stochastic resonance system.

Step 3: The parental individual was randomly generated and decoded to obtain a and b. Substituting it into the stochastic resonance system, according to the fitness function, the parent individuals are screened, crossed and mutated to generate offspring individuals. As the genetic algorithm optimizes parameters a and b, the fitness function gradually converges, and the output is the optimal combination of parameters.

Step 4: The optimal parameters a and b were substituted into the stochastic resonance system. The optimized stochastic resonance system was used to extract the weak signal features.

Step 5: Set the Fully connected neural network structure and set parameters such as network depth, number of neurons at each layer, and learning rate. Then set the appropriate cost function and optimization strategy based on different task requirements.

Step 6: Layer-by-layer training Fully connected neural network, the upper network output as lower network input to extract feature information; Then, the output of the last layer network is used as the input of the Softmax classifier to calculate the diagnosis result; Finally, the diagnosis results are compared with the sample tags, and the parameters such as weights and offsets of the networks are fine tuned by the back propagation algorithm.

Step 7: Test Fully connected neural network diagnostic accuracy. Input test data to calculate whether the diagnostic results meet the actual expected diagnostic accuracy (above 96%). If the diagnostic accuracy is too low, correct the Fully connected neural network structure and repeat Steps 5 and 6 until the desired accuracy is achieved.

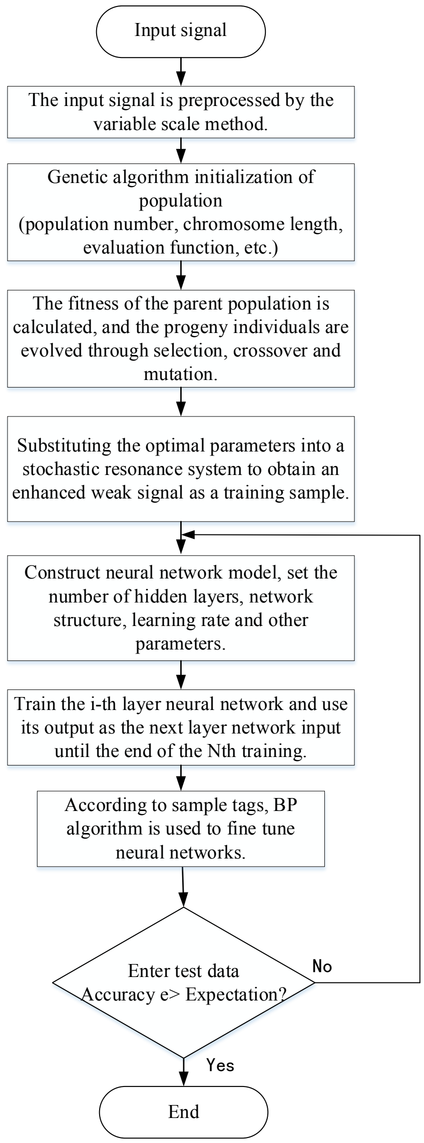


Figure 6: Process of rolling bearing weak fault diagnosis

4 Experimental verification

The simulation results show that the signal characteristics are effectively enhanced after AGSR processing. For the original signal, although the signal solved by Langevin equation retains the frequency characteristics of the original signal, it is uncertain whether the new signal has the ability to identify different fault. Therefore, in order to verify the actual effect of the AGSR method on the early fault diagnosis of rolling bearings, this paper uses the bearing fault data of the Case Western Reserve University Bearing Data Center for analysis. As shown in Fig. 7, the experimental platform consists of a motor, a torque sensor, a power tester, and an electrical control device. The sensor is mounted above the drive-end bearing seat.

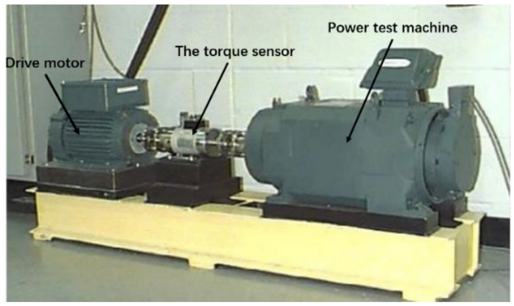


Figure 7: Rolling bearing experimental platform

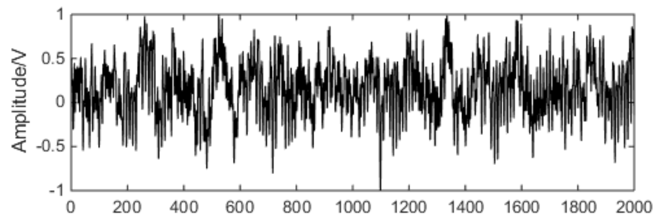
The type of drive end bearing is SKF6205, and the bearing uses electric spark technology to process single point damage. A pitting of 0.178 mm diameter is set on the bearing inner ring, outer ring and rolling body, and the sampling frequency is 48 kHz. The 4 bearing states used in the test are shown in Tab. 1.

Table 1: 4 states of rolling bearing

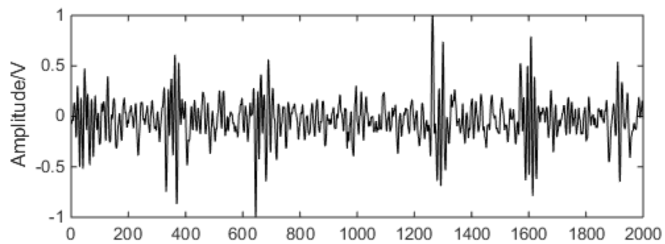
Bearing state	Sample number	State label	Fault category
Normal	2000	1000	1
Innerring fault	2000	0100	2
Outerring fault	2000	0010	3
Ball fault	2000	0001	4

4.1 Processing of experimental data

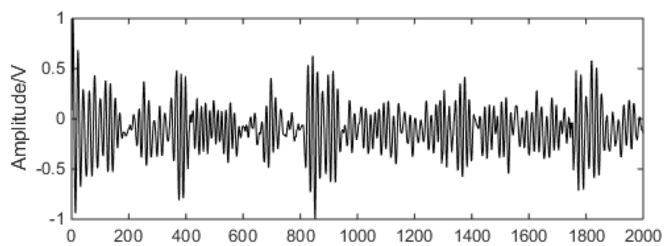
Divide the data obtained from the experimental platform, randomly select 20% of the total sample data of each type as test data, and use the remaining 80% as training data. Therefore, each type of data has 1600 training samples and 400 test samples. Each sample contains 2000 continuous data sampling points. The time domain signal waveforms of the four states of the bearing [Jiang, Chen and Dong (2013); Shen and Yang (2006)] are shown in Fig. 8.



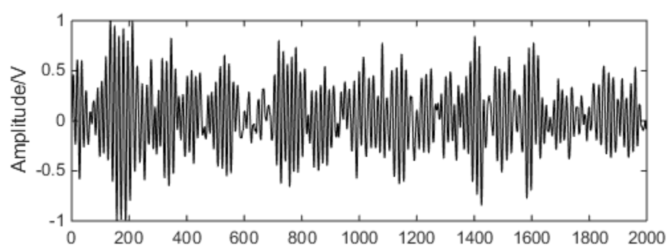
(a) Normal



(b) Inner ring fault



(c) Outer ring fault

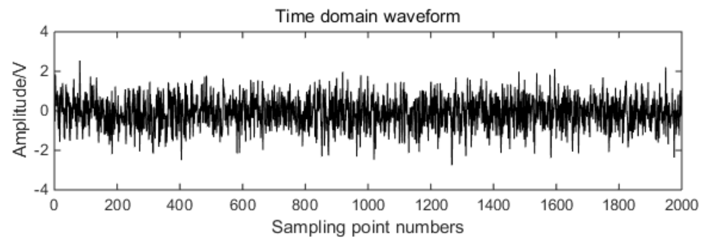


(d) Ball failure

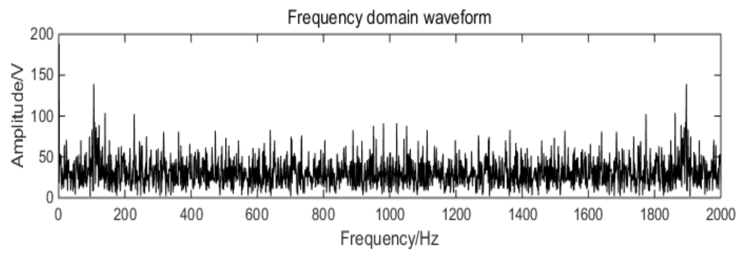
Figure 8: Rolling bearing weak fault vibration waveform

4.2 Improved random resonance signal preprocessing

Considering the influence of background noise in practical working conditions, Gauss white noise with D=0.3 noise intensity is added to the normalized vibration signal. the time-domain waveform and spectrum of the noisy signal are shown in Fig. 9. From the time domain waveform, it can be seen that the bearing fault features are completely submerged by the noise, and there is no obvious feature spectrum peak in the spectrum diagram, so it is impossible to judge whether the bearing has a fault.



(a)



(b)

Figure 9: Rolling bearing outer ring fault signal

This paper uses AGSR method to preprocess the signal. Firstly, linearly compress the signal and set the frequency compression ratio to R=50. Then, in the genetic algorithm, let the population size G=100, the chromosome length L=17 and the Evolution times K=50, and the parameters a and b to be optimized range from [0-1000]. Fig. 10 shows that the fitness function of the improved stochastic resonance system converges after 50 iterations, and the optimization result is a=73.85, b=273.29, and SNR=-1.21.

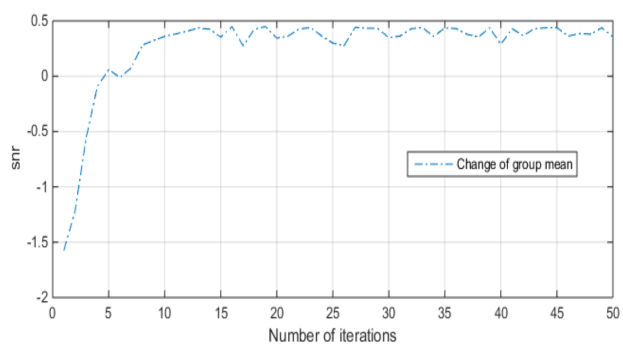
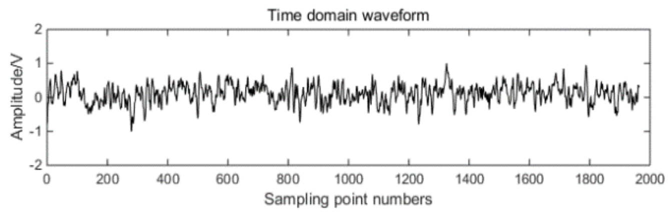


Figure 10: Fitness function optimization

The optimized parameters are substituted into the stochastic resonance system. The resulting signal waveforms and spectrum are shown in Fig. 11. The signal processed by the AGSR method is seen in the figure, and its time domain signal (Fig. 11(a)) is more regular. In addition, from Fig. 11(b), it is found that there are two frequency band amplitudes greater than the remaining components, which can be used as an extracted outer ring fault feature for pre-processing fault diagnosis [Wang, He and Kong (2014)].



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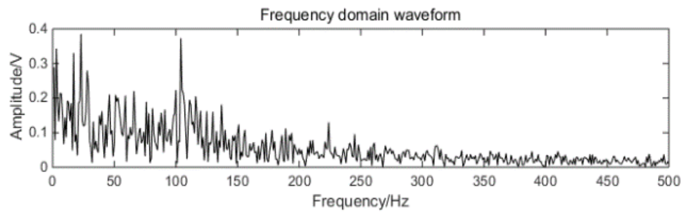

(b)

Figure 11: AGSR output time frequency diagram

Similarly, in order to prove once again that the AGSR method is superior to the stochastic resonance method, this paper adopts the traditional stochastic resonance method to process the fault signal, and the output waveform is shown in Fig. 12. As can be seen from the figure, the conventional stochastic resonance method is limited by the adiabatic approximation theory and cannot handle high-frequency signals, and the output signal is severely distorted, making it difficult to determine the bearing failure based on the output waveform.

Figure 12: The output of stochastic resonance system

4.3 Bearing weak fault diagnosis

The time-frequency and frequency-domain of the vibration signal contain rich feature information. The experimental data is preprocessed using the SR method and the AGSR method. Three kinds of samples are selected for the training of fully connected neural network, and the diagnosis results are analyzed by selecting the time domain signal extracted by the traditional method and the signals (the time domain and frequency domain signals) extracted by the improved method (the Fourier transform of the time domain signal). And analyze the diagnosis results.

Five-layer fully connected neural network was constructed. The network model was 2000-300-100-50-4. the model indicates that each sample contains 2000 points in the network input, the number of nodes in the middle three hidden layers is 300, 100 and 50, and the last 4 types of fault labels are output. The training methods of the fully connected neural network are as follows:

1) Initialize the network parameters and enter training samples. The input format of the sample is 6400×2000, and the number of training samples is M=6400. The number of neurons in the second layer of the model is 300, so the corresponding weight matrix is 2000×300, Afterwards, the weight of each layer is similarly derived.

2) The samples are normalized and input into the fully connected neural network to start training. With the objective of minimizing the loss function, the weights are adjusted by gradient descent and back propagation algorithm step by step.

3) Fully connected neural network model training is completed and tested. Enter the test set to test the diagnostic accuracy of the network, and adjust the network structure and parameters again according to the diagnostic accuracy rate until the actual requirements are met.

Tab. 2 is the result of fault diagnosis of rolling bearing with fully connected neural network under different pretreatment methods. From Tab. 2, it can be seen that the fault recognition rate of the time domain signal extracted by the traditional random resonance method is only 45.32%, which verifies the conclusion that the traditional method is difficult to extract the high frequency signal. When the time domain signal extracted from the improved stochastic resonance method is used as a sample, the ability to identify weak faults is higher than that of traditional methods. But even if we constantly adjust the network structure and dropout parameters, its classification accuracy is still less than 70%.

Table 2: Performance comparison between SR and AGSR algorithm

Preprocessing method	Input signal	Total sample size	Accuracy rate
SR method	Time domain signal	8000	45.32%
AGSR method	Time domain signal	8000	64.31%
AGSR method	Frequency domain signal	8000	98.36%

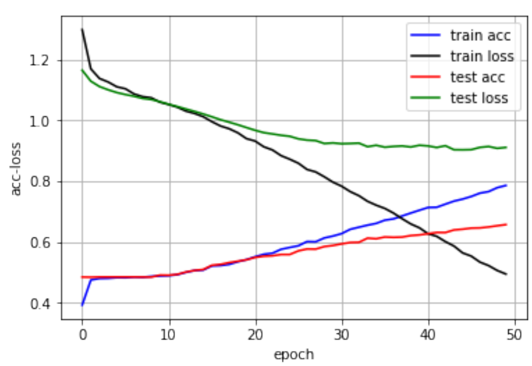

Figure 13: Fitness function optimization

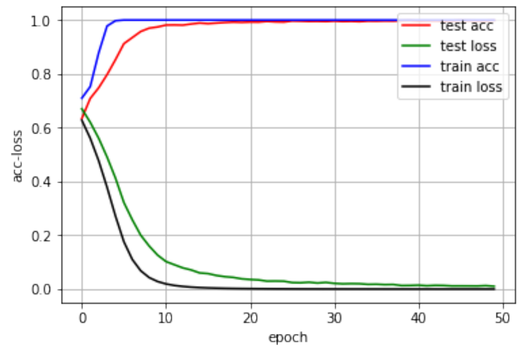

Figure 14: Fitness function optimization

As shown in Fig. 13, the results show that the time domain signal contains some fault information, but because of its time-varying features, the fault information contained in each sample is not the same. It is difficult to meet the actual demand for the weak fault diagnosis. When the frequency domain signal extracted from the AGSR method is taken as a sample, it can be seen from Fig. 14 that the fault recognition rate reaches 98.36% on the test set. The loss of the training set and the test set decreased synchronously, and there was no over-fitting phenomenon.

5 Conclusions

In this paper, an early fault diagnosis method for rolling bearings based on improved stochastic resonance preconditioning is studied. Using SR to process weak signals and using signal-to-noise ratio as a measure of system parameter optimization, the time- and frequency-domain feature-input fully connected neural networks of bearing experimental data were extracted to enable early fault diagnosis and analysis. In addition, the feature set of the improved stochastic resonance extraction has better classification performance and higher classification accuracy than traditional methods, which provides a new method for fault diagnosis and early failure.

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Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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