

## *Retraction*

# **Retracted: Theory and Application of Weak Signal Detection Based on Stochastic Resonance Mechanism**

### **Security and Communication Networks**

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

### **References**

- [1] L. Cui, J. Yang, L. Wang, and H. Liu, "Theory and Application of Weak Signal Detection Based on Stochastic Resonance Mechanism," *Security and Communication Networks*, vol. 2021, Article ID 5553490, 9 pages, 2021.

## Research Article

# Theory and Application of Weak Signal Detection Based on Stochastic Resonance Mechanism

**Lin Cui** , **Junan Yang**, **Lunwen Wang**, and **Hui Liu**

*College of Electronic Engineering, National University of Defense Technology, Hefei 230037, Anhui, China*

Correspondence should be addressed to Lin Cui; [cuilin17@nudt.edu.cn](mailto:cuilin17@nudt.edu.cn)

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Stochastic resonance is a new type of weak signal detection method. Compared with traditional noise suppression technology, stochastic resonance uses noise to enhance weak signal information, and there is a mechanism for the transfer of noise energy to signal energy. The purpose of this paper is to study the theory and application of weak signal detection based on stochastic resonance mechanism. This paper studies the stochastic resonance characteristics of the bistable circuit and conducts an experimental simulation of its circuit in the Multisim simulation environment. It is verified that the bistable circuit can achieve the stochastic resonance function very well, and it provides strong support for the actual production of the bistable circuit. This paper studies the stochastic resonance phenomenon of FHN neuron model and bistable model, analyzes the response of periodic signals and nonperiodic signals, verifies the effect of noise on stochastic resonance, and lays the foundation for subsequent experiments. It proposes to feedback the link and introduces a two-layer FHN neural network model to improve the weak signal detection performance under a variable noise background. The paper also proposes a multifault detection method based on the total empirical mode decomposition of sensitive intrinsic mode components with variable scale adaptive stochastic resonance. Using the weighted kurtosis index as the measurement index of the system output can not only maintain the similarity between the system output signal and the original signal but also be sensitive to impact characteristics, overcoming the missed or false detection of the traditional kurtosis index. Experimental research shows that this method has better noise suppression ability and a clear reproduction effect on details. Especially for images contaminated by strong noise ( $D = 500$ ), compared with traditional restoration methods, it has better performance in subjective visual effects and signal-to-noise ratio evaluation.

## 1. Introduction

The principle of stochastic resonance applied to weak signal enhancement detection has practical application value, and it is also a new technology, which can realize the state monitoring and early fault diagnosis of electromechanical equipment, and has important economic significance for ensuring the reliable operation of electromechanical equipment and preventing malfunction. However, the working environment of electromechanical equipment is very harsh. The early weak faults are accompanied by complex mechanical interference and environmental noise, making early fault detection difficult. Therefore, it can be said that the monitoring of the operation of mechanical equipment has always been the current fault detection, being one of the hotspots and difficulties.

The application of adaptive stochastic resonance principle for weak signal enhancement detection is a new technology with practical application value, and many foreign scholars have studied it. For example, Zhi-Hui adopts adaptive stochastic resonance technology under short data set conditions. The weak sine signal in strong noise is extracted, and it is also proposed that this method can also detect chirp, pulse amplitude modulation, frequency shift keying, and pulse width modulation signals under white noise [1]. Hongyan proposed the concept of adaptive stochastic resonance. Its essence is to adopt the method and theory of noise adaptive adjustment of stochastic resonance. Its goal is to solve the best noise level and which signal and which type of noise produce the best. “Stochastic resonance” problem, noise adjustment method, and theory of adaptive stochastic resonance have greatly promoted the development of stochastic resonance theory

and application [2]. Arathi and Rajasekar analyzed the stochastic resonance phenomenon of a symmetric three-well system at different potential well depths. Huiqing Zhang et al. studied a three-potential well logic SR system in a non-Gaussian noise environment. Without changing the system characteristics, the system can generate all logic states, and whether it is multiplicative noise or additive noise, it will affect the potential. Function shape has a big impact [2]. Compared with the traditional method, the difference is that stochastic resonance uses noise to enhance useful signals in a nonlinear system and then realizes weak signal enhancement detection, so this detection method can well retain the details of the signal, and there is no damage to the characteristic signal. It provides a new method for detecting fault characteristics.

In the research carried out by Chinese scholars, Blankenburg proposed an adaptive stochastic resonance method based on ant colony algorithm, which uses the multiparameter parallel ability of ant colony algorithm to obtain the best matching state of the system, and has powerful processing functions. The faint signal in the noise has been validated by simulation test and engineering application of early fault diagnosis of locomotive bearings [3]. Park designed a bistable adaptive stochastic resonance system. The system uses a linear random search algorithm to change the barrier height by fixing the system parameter  $b$  and adjusting the system parameter to obtain the best state of the stochastic resonance system. To extract weak periodic signals, the author also successfully used this method to extract weak fault signals from switching power supplies [4]. Dettmer designed the bistable stochastic resonance based on parameter adjustment and its adaptive control hardware circuit system, which verified the feasibility of the adaptive stochastic resonance method in practical engineering measurement. The above adaptive stochastic resonance method mainly optimizes a single parameter, but this ignores the interaction between the parameters. When the fixed parameter selection is not appropriate, the optimal resonance state cannot be achieved [5].

This paper studies the influence of nonlinear bistable system parameters on stochastic resonance and the characteristics of bistable stochastic resonance circuit and its Multisim simulation realization. Based on this research, an adaptive control bistable system parameter system is realized through the microcontroller AVR single-chip microcomputer to realize stochastic resonance; the hardware circuit of the adaptive stochastic resonance system is built, including bistable stochastic resonance circuit, A/D conversion circuit, voltage polarity conversion circuit, and power supply circuit. Finally, the signal detection system is in the laboratory. Experimental tests were carried out in the environment, which verified that the signal detection system can effectively realize weak signal detection under a specific noise background.

## 2. Weak Signal Detection Theory and Application Based on Stochastic Resonance Mechanism

*2.1. Basic Theory of Stochastic Resonance.* Stochastic resonance is a nonlinear dynamic phenomenon produced by the

synergy of the three basic elements of weak periodic signal, noise, and nonlinear system. It can effectively realize the transfer of noise energy to signal energy instead of simply suppressing noise. This phenomenon provides a powerful means for people to use the stochastic resonance theory to obtain weak signal information from the background of noise [6, 7].

*2.1.1. Stochastic Resonance Model of Bistable System.* In the study of stochastic resonance, the nonlinear bistable system described by the Langevin equation is a classic model for studying stochastic resonance, which can be expressed as follows:

$$\dot{x}(t) = -U(x) + A \sin \omega t + \Gamma(t). \quad (1)$$

In formula (1),  $A \sin \omega t$  is the weak periodic signal to be measured with amplitude  $A$  and frequency  $\omega$  and  $U(x)$  is the potential function of the bistable system:

$$U(x) = -\frac{ax^2}{2} + \frac{bx^4}{4} - xA \sin \omega t. \quad (2)$$

In the formula,  $a$  and  $b$  are the structural parameters of the bistable system and  $a > 0$  and  $b > 0$ .

*2.1.2. Immersion and Elimination Theory.* Since the adiabatic approximation condition is the hypothesis of the theory, the theory is also called the adiabatic approximation theory. The adiabatic approximation condition is that the input weak periodic signal and noise intensity are both very small; that is,  $A \ll 1$ ,  $f \ll 1$ ,  $D \ll 1$ . At this time,  $x = 0$  divides the entire  $x$  area into two parts  $(-\infty, 0)$  and  $(0, \infty)$ . The probability distribution in the corresponding area is

$$\begin{aligned} P_-(t) &= \int_{-\infty}^0 p(x, t) dx, \\ P_+(t) &= \int_0^{\infty} p(x, t) dx. \end{aligned} \quad (3)$$

In the formula,  $P_-(t) + P_+(t) = 1$ .

*2.2. Basic Bistable Stochastic Resonance Circuit and Its Multisim Simulation.* Since the operational amplifier can easily implement some common mathematical operations with peripheral resistance-capacitance components, the bistable circuit system can be built through the operational amplifier. For stochastic resonance systems, the following Langevin equation can be used to describe

$$\dot{x}(t) = ax(t) - bx^3(t) + A \sin \omega t + \Gamma(t). \quad (4)$$

In the formula,  $A \sin \omega t$  is the periodic signal and  $\Gamma(t)$  is the white noise. The sum of the two can be regarded as the measured engineering signal. In order to realize the abovementioned first-order differential equation, the operational amplifier integrator is used to realize it; that is, formula (4) becomes

$$x = \int (ax(t) - bx^3(t) + A \sin \omega t + \Gamma(t)dt). \quad (5)$$

It can be seen from formula (5) that Langevin's equation is composed of an integral part, a multiplication part, and an addition part. The design of electronic circuits can be realized by the corresponding integration circuit, proportional multiplication circuit, and addition circuit.

**2.3. Overall Hardware Design Scheme.** In order to realize the adaptive control and adjustment of the parameters of the bistable system, this article uses the AVR single-chip microcomputer to drive and control the digital potentiometer AD7376, adjust the resistance divider ratio in the bistable stochastic resonance circuit through the code of AD7376, and then change the bistable system parameters  $a$  and  $b$ , making the system produce stochastic resonance [8, 9]. The system is mainly composed of AD7376 bistable stochastic resonance circuit, A/D conversion circuit, voltage polarity conversion circuit, power supply circuit, and AVR single-chip microcomputer module. The specific implementation steps of the system are as follows:

- (1) Input the signal to be measured with noise into the stochastic resonance circuit system
- (2) The signal after passing through the system is a bipolar signal, which requires voltage polarity conversion
- (3) Converted into 0~5 V voltage signal by voltage polarity conversion circuit
- (4) A/D conversion of the conditioned signal
- (5) The AVR single-chip computer samples and analyzes the converted signal
- (6) The AVR single-chip computer determines whether the system is in resonance through the resonance determination program
- (7) Enable adaptive search algorithm to drive and adjust AD7376 to achieve system resonance

**2.4. Stochastic Resonance Mechanism in the Nervous System.** The Hodgkin-Huxley (HH) neuron model, because it first satisfies the electrophysiological characteristics of the neuron, can better describe the relationship between the membrane potential and the membrane current in the axon of the neuron, and it conforms to the law of generation and transmission of action potentials. It is a classic model of excitable cells. The FitzHugh-Nagumo model, as a simplification of the H-H neuron model, is a simplified typical model of excitable neurons and has received extensive attention in the field of neural engineering [10, 11].

**2.4.1. FitzHugh-Nagumo Neuron Model.** This model can describe many characteristics of nerve and myocardial fiber electrical impulses, such as the existence of excitation threshold, relative and absolute recovery periods, and the generation of pulse trains under the action of external

currents [12, 13]. At the same time, because the FHN neuron model is a simplification of the H-H neuron model, it is a simple two-variable form, retaining the main characteristics of the excitable nerve cell regeneration excitation mechanism, and is widely used to study the properties of the excitable system and the law of spiral waves. The model can be described by the equations as follows:

$$\begin{cases} \varepsilon \frac{dv}{dt} = v(v-a)(1-v) - w + A_T - B + I_{\text{ext}}, \\ \frac{dw}{dt} = v - w - b, \end{cases} \quad (6)$$

where  $v$  represents the rapidly changing neuron membrane voltage;  $w$  is the slowly changing recovery variable;  $\varepsilon$  is the time constant, which determines the firing rate of the neuron;  $A_T$  is the critical value, prompting the neuron to fire regularly;  $B$  is the average signal level and the difference of  $A_T$ ;  $a$  and  $b$  are the equation constants;  $I_{\text{ext}}$  is the external current input.  $I_{\text{ext}} = S(t) + \xi(t)$ , where  $S(t)$  is the input signal and  $\xi(t)$  is the noise.

**2.4.2. Stochastic Resonance Evaluation Method.** The evaluation indicators of stochastic resonance currently mainly include signal-to-noise ratio, mutual information rate, and cross-correlation coefficient. Among them, the traditional signal-to-noise ratio can be used to measure the stochastic resonance effect of periodic excitation; mutual information rate, as a quantitative tool to describe the degree of information association in information theory, has been widely used in the study of periodic and nonperiodic stochastic resonance phenomena. The cross-correlation coefficient method is used to study the phenomenon of nonperiodic stochastic resonance to measure the matching relationship between the input and output signals of the system [14, 15]. The above evaluation methods are all quantitative stochastic resonance from their own perspectives. Although the evaluation results are not the same, they all have certain rationality. Therefore, this paper selects the signal-to-noise ratio and the mutual information rate as the evaluation indicators of the stochastic resonance effect under periodic excitation and selects the mutual information rate and the cross-correlation coefficient as the evaluation indicators of the stochastic resonance effect under the nonperiodic excitation, in order to evaluate the stochastic resonance from multiple angles. The effect is judged [16, 17].

The signal-to-noise ratio is a traditional method of evaluating stochastic resonance, which is based on the analysis of the neuron response signal spectrum.

The signal-to-noise ratio is defined as

$$\text{SNR} = 10 \log_{10} \left( \frac{S}{B} \right). \quad (7)$$

Among them,  $S$  and  $B$ , respectively, represent the peak value of the response signal and the intensity of the floor noise at the corresponding input periodic excitation frequency in the power spectral density, and the unit of the signal-to-noise ratio is decibel (dB). Calculating the power

spectral density is the result of the accumulation and averaging of several power spectral densities; that is, several data segments of the same time length are obtained under the same input stimulus signal and noise intensity, and the power spectral density is calculated separately for each data segment. Then, after accumulating and averaging the power spectral density of all data segments, the desired result can be obtained. This can weaken the irregular fluctuations in the power spectral density graph, thereby reflecting an average frequency characteristic of the neuron response signal over a long period of time [18, 19].

*2.5. Adaptive Stochastic Resonance Process of Weak Shock Signal Based on Knowledge-Based Particle Swarm Algorithm.* Based on the knowledge of basic characteristics or principles, combined with particle swarm algorithm, a knowledge-based particle swarm algorithm adaptive stochastic resonance detection method for weak shock signals is constructed. The core of this method to improve optimization is that when the stochastic resonance particles do not transition, the fitness value of the individual particles in the particle swarm algorithm is evaluated according to the adopted kurtosis index, and when the stochastic resonance particles transition, the individual in the particle swarm algorithm is directly. The fitness value of the particle is assigned zero, eliminating the time-consuming process of calculating the output of the stochastic resonance system through the Runge–Kutta method and evaluating the fitness value of the particle according to the kurtosis index [20, 21]. For the detection of weak pulse signals, the knowledge-based particle swarm algorithm is used to synchronously optimize the structural parameters  $a$  and  $b$  of the nonlinear bistable stochastic resonance system, and the fitness function is the kurtosis index. The following describes the necessary points of this method.

- (1) Judgment of transition of resonant particles: when the particles of the bistable system transition, the value of the system output  $x(t)$  changes from positive to negative or from negative to positive. Assuming that the number of sampling points is  $N$ , the output is the number of positive values accumulated and recorded as  $Np$ . When  $Np$  satisfies  $Np \in [N_{\min}, N_{\max}]$ , it is considered that the system has transitioned.
- (2) Reference barrier  $U_l$ : when the potential barrier is equal to this value, the particles of the stochastic resonance system can transition. Obviously, when the potential barrier is less than the reference barrier value, the particles of the stochastic resonance system can also transition [22].
- (3) The study found that the stochastic resonance appears near the lowest point of a certain potential barrier when detecting the shock signal. Therefore, the detected shock signal will have abrupt changes near the initial point until the system keeps up with the change of the signal, change near the lowest point of a potential barrier. Therefore, the value near the

initial point should be avoided when calculating the relevant indicators, and the calculation of the previous  $i = 50$  points should be avoided in the article.

## 2.6. Measures of Stochastic Resonance

*2.6.1. SNR and SNR Gain.* The signal-to-noise ratio and signal-to-noise ratio gain occupy an extremely important position in the stochastic resonance measurement index. The definition of signal-to-noise ratio is the ratio of the amplitude of the system output signal frequency to the background noise of the same frequency.

$$\text{SNR} = \lim_{\Delta w \rightarrow \infty} \int_{w-\Delta w}^{w+\Delta w} \frac{S(w)}{S_N(w)} dw, \quad (8)$$

where  $S(w)$  is the signal power spectral density;  $S_N(w)$  is the noise power spectral density near the signal frequency.

*2.6.2. Symbol Sequence Entropy Method.* The signal-to-noise ratio and the signal-to-noise ratio gain need to have a good estimate of the characteristic signal when describing stochastic resonance. Because it is difficult to estimate the signal-to-noise ratio in practice, the signal-to-noise ratio is based on the amplitude at the characteristic frequency and the same frequency. The ratio of background noise is local, and the output signal cannot be measured as a whole [23, 24]. However, the residence time distribution is very complicated, not easy to quantify, and difficult to achieve in engineering applications. In order to solve the above problems, symbol sequence entropy is proposed as a measure of stochastic resonance output, and an adaptive stochastic resonance system is designed to detect weak signals.

Symbol sequence analysis is a “coarse-grained” process by turning a data sequence of multiple possible values into a symbol sequence with only a few different values. This process can capture signals with a deterministic structure, especially the period, or modulation signal characteristics, so it is suitable for mechanical failure signal analysis. The above comparison shows that, for a signal with a deterministic structure, its sequence entropy must be a certain value to some extent, while for a signal containing noise or a pure noise signal, its entropy must be greater than or close to 1. Through the above analysis, we know that, in the process of detecting weak stochastic resonance signals and adjusting the system parameters  $a$  and  $b$  to make the system output tend to be the best output, the entropy value of the system output signal will tend to the entropy value of the original pure signal. At this time, the output signal-to-noise ratio of the system will reach the maximum, and the amplitude of the detected weak signal will also reach the maximum; that is, the conversion of noise energy to the frequency of the periodic driving force reaches the maximum.

*2.7. Stochastic Resonance Dynamic Behavior Mechanism.* Under certain conditions, increasing the noise intensity can make the output of the stochastic resonance system better

highlight the components of the original input signal. This article discusses in depth the dynamic behavior of stochastic resonance systems under the combined action of signal and noise and then analyzes the mechanism of stochastic resonance from a qualitative perspective.

*2.7.1. Transition Behavior Led by Large-Value Incentives.* Because there is a process greater than the system transition threshold in the excitation signal, a transition process occurs. We summarize this process as the behavior of “large value leading the transition”; that is, if the signal added to the system has a process beyond the transition threshold, then this process will lead to another subsequent process within the transition threshold. The output of the latter follows the former to occur near the same side of the attractor curve. This nature is very interesting. It can be illustrated with an image metaphor: for example, if there are two identical teams, due to the different nature of the “leader brother,” the nature of the two teams is also different. Moreover, image processing based on stochastic resonance effectively utilizes this property to highlight the information of certain characteristic patterns.

*2.7.2. Subinterference and Major Interference Caused by Noise.* When the value of the noise-containing signal is between the horizontal lines A and B, the system currently has two attractor curves. At this time, the system will only firmly pull the moving points that belong to its own attraction domain to its side, and it is impossible to move it. The moving point in the other attraction domain is also attracted to its side, so the state of the system tends to be stable at this time. Since the movement trend of the moving point at this moment is highly consistent with the attractor at all times, this type of interference will not induce a transition. In other words, when the signal amplitude of the noise is within the system threshold, these interferences cannot induce the system to produce transition behaviors. We call this type of interference “subinterference.” Similarly, considering that Gaussian white noise has zero mean, in the absence of transitions, these disturbances are often oscillating motions that make the moving point back and forth near the equilibrium point; even during the transition, due to its insufficient motion amplitude to counter the big interference, this type of subinterference will not change the transition trend.

At the same time, we still need to point out that, for systems with high noise intensity, there will be a large proportion of the interference amplitude with a large value, and their effect is likely to make the moving point occur easily and directly. We call this type of interference “overinterference”; this type of overinterference can easily lead to the phenomenon of “over-stochastic resonance.”

### 3. Experimental Research on Weak Signal Detection Based on Stochastic Resonance Mechanism

*3.1. Design and Manufacture of Noise Sources.* During the experiment of stochastic resonance circuit, a noise source with variable noise intensity is needed to provide noise to the system and simulate the background noise of actual engineering signals. This text uses AT89C4051 one-chip computer system to realize a Gaussian white noise source that can meet the experimental requirement.

The smallest system module of the single-chip microcomputer provides an executable program platform for the single-chip microcomputer. The single-chip microcomputer generates pseudorandom numbers that obey the Gaussian distribution; the D/A conversion module converts the pseudorandom numbers into Gaussian noise voltages with fixed variance; then we need to process the waveform adjustment module. The DC quantity and amplitude are adjusted and output.

#### 3.2. Experimental Method

*3.2.1. Initialization.* Estimate the system parameters  $a$ ,  $b$ , and  $\bar{H}_s$  according to the measured periodic signal and background noise intensity, and set initial values for  $a$  and  $b$ ; try to make the barrier height as small as possible for subsequent adjustments; set the division threshold for symbol sequence conversion  $p$ , to prepare for subsequent symbolization. This article uses the most common threshold that  $p$  is equal to zero.

*3.2.2. Symbolization of Time Series.* The mechanical vibration signal collected by the sensor is used as the input of the bistable stochastic resonance system, and the fourth-order Runge–Kutta method is used to solve the Langevin equation to obtain the output signal. The calculation step takes the reciprocal of the sampling period of the signal to obtain the time series  $\{x_i\}$  and discretize it into a sequence  $\{x(n)\}$ ; set an appropriate time interval  $\Delta t$ , and filter  $\{x(n)\}$  through a threshold function according to the set threshold  $p$ , and convert the time series into a symbol sequence  $s(n)$ .

*3.2.3. Calculating the Improved Shannon Information Entropy.* Determine the symbol sequence length  $L$ , generally 3–8 in engineering. This paper uses  $L=5$ ,  $\Delta t=0.001$  to generate a short sequence  $\{\hat{s}(L)\}$ ; sequence the symbol sequence  $\{\hat{s}(L)\}$  to form decimal sequence  $s(L)$  based on ten. Calculate the probability  $p_{i,L}$  of the symbol sequence code, and calculate Shannon information entropy  $H_s$  according to the formula.

*3.3. Establishing a Model Evaluation Index System.* The evaluation index is a specific evaluation item determined according to some evaluation goals, which can reflect some

basic characteristics of the evaluation object. The index is specific and measurable, and it is the observation point of the goal. Definite conclusions can be drawn through actual observation of the object. Generally speaking, the evaluation index system includes three levels of evaluation indexes: they are the relationship between gradual decomposition and refinement. Among them, the first-level evaluation index and the second-level evaluation index are relatively abstract and cannot be used as a direct basis for evaluation. The third-level evaluation indicators should be specific, measurable, and behavior-oriented and can be used as a direct basis for teaching evaluation.

**3.4. Determining the Evaluation Weight.** The index weight is a numerical index indicating the importance and function of the index. In the indicator system of the evaluation plan, the weight of each indicator is different. Even if the indicator level is the same, the weight is different. Index weight is also called weight and is usually represented by  $a$ . It is a number greater than zero but less than 1, and the sum of the weights of all first-level indicators must be equal to 1, that is, satisfying the conditions  $0 < a < 1$  and  $\sum a = 1$ .

#### 4. Experimental Research and Analysis of Weak Signal Detection Based on Stochastic Resonance Mechanism

**4.1. Relationship between System Structural Parameters and Stochastic Resonance.** Suppose signal  $s(t) = A \cos(2\pi f_1 t) + \text{noise}$ , sampling frequency  $f_s = 5$  Hz, sampling time  $t = 500$  s, signal frequency  $f_1 = 1$  Hz, signal amplitude  $A = 0.06$ , noise is Gaussian with intensity  $D = 2$ , white noise, and the number of sampling points is 3000. Next, analyze the changes of system parameters and the evolution process of the system entering the stochastic resonance state, and use simulation experiments to illustrate the changes in the time domain waveform and frequency spectrum of the output signal of the stochastic resonance bistable system as the system parameters  $a$  and  $b$  change. The experimental results are shown in Figure 1.

In Figure 1, (a) is the time-domain waveform of the periodic driving force, which is a cosine periodic signal; (b) is the corresponding frequency spectrum. It can be seen that its frequency is a given 0.02 Hz without any noise frequency interference. Adding Gaussian white noise with a noise intensity of 4, it can be found that the time-domain waveform has been completely deformed without any regularity. At the same time, a weak characteristic signal frequency of 0.02 Hz can be found from the spectrum of the picture species, and its amplitude is about 0.14. In addition, there is a lot of noise interference. The frequency of noise in certain places is far greater than the characteristic frequency of the signal, which makes it difficult to determine which frequency is the signal frequency to be extracted, causing a certain amount of confusion.

The noise-added signal is used as the input of the nonlinear bistable system, and the fourth-order Runge-Kutta method is used to calculate the output signal of the

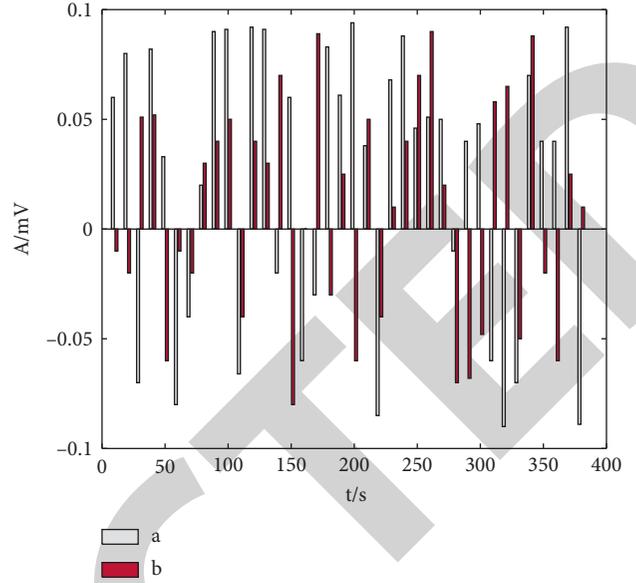
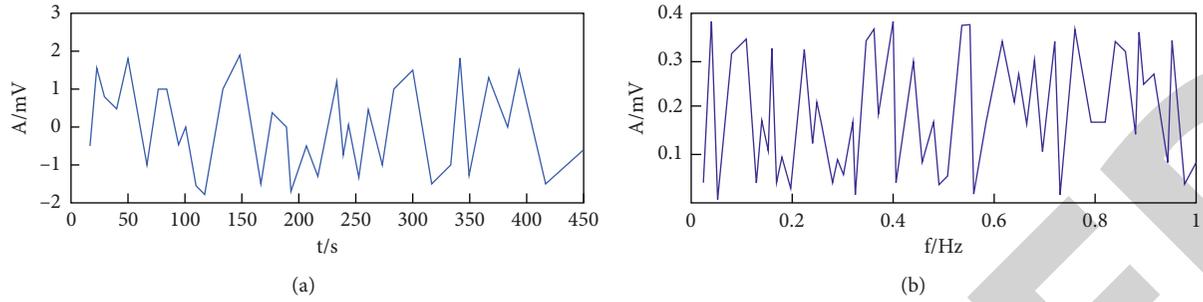


FIGURE 1: Periodic driving force and time spectrum after adding noise.

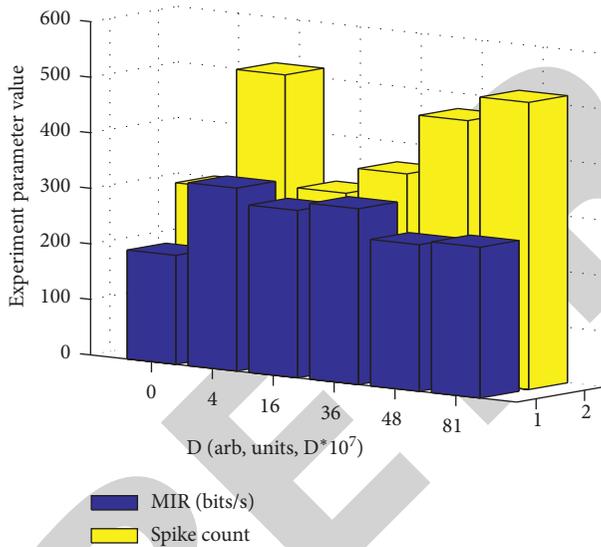
system, and the iteration step is  $h = 1/f_s$ .  $a = 0.2$ ,  $b = 0.4$  to get the time spectrum of the system output as shown in Figure 2.

The time-domain waveform (a) has a certain degree of certainty and periodicity, but it is not obvious, while the amplitude of the characteristic frequency in the spectrogram (b) is increased from 0.11 to 0.33, which is about 3 times higher. At the same time, the noise is greatly attenuated, and most of its frequencies are concentrated in the range of 0 to 0.3 Hz. It can be said that stochastic resonance compresses the frequency band of noise in a large range. In the stochastic resonance method, under the assumptions of the adiabatic approximation theory, the enhancement effect of the periodic driving force of different small frequencies is different, that is to say, even under the same system parameters; the amplitude of the periodic driving force is the same. At different times, the final enhancement effect is also different, so the stochastic resonance method has certain selectivity to the frequency of the signal.

**4.2. Weak Signal Detection Results of the Open-Loop Double-Layer FHN Stochastic Resonance Model.** The key factor of signal restoration is to reconstruct the relative change law of the original signal with respect to time. In this paper, the response amplitude of the FHN neuron model generally reflects the sensitivity of the system to weak signal input, and the firing frequency of the model's action potential can indirectly describe the abovementioned relative changes. Therefore, in addition to the quantitative analysis of the single FHN model and the double-layer FHN model by using the signal-to-noise ratio, the cross-correlation coefficient, and the mutual information rate, this paper also introduces the number of pulses and the average pulse amplitude to evaluate the above neuron model. The experimental results are shown in Table 1.

FIGURE 2: Frequency spectrum of system output when  $a=0.2$ ,  $b=0.4$ .TABLE 1: Under the aperiodic signal input condition of  $A = 0.05$ , the corresponding relationship between the number of pulses output by the double-layer neuron and the noise intensity.

$D$ (arb. units, $D^* 10^7$ )	0	4	16	36	48	81
Correlation	0.2643	0.2746	0.3017	0.2846	0.1836	0.1648
MIR (bits/s)	196.2	329.34	301.28	316.49	263.84	271.48
Spike_count	302	518	317	364	472	517

FIGURE 3: Under the aperiodic signal input condition of  $A = 0.05$ , the corresponding relationship between the number of pulses output by the double-layer neuron and the noise intensity.

As can be seen in Figure 3, when the noise intensity increases to between 4 and 36, the evaluation indicators such as the signal-to-noise ratio, mutual information rate, and cross-correlation coefficient of the two-layer neuron network reach a high value, and the response pulse increases significantly. The stochastic resonance phenomenon is significant; with the continuous increase in the noise ( $D = 48, 81$ ), it can be seen from the evaluation index that the performance of the neuron network model has deteriorated, and at the same time, the response pulse is too much, covering the law of the original signal, making the stochastic resonance phenomenon weaker. It can be seen that noise

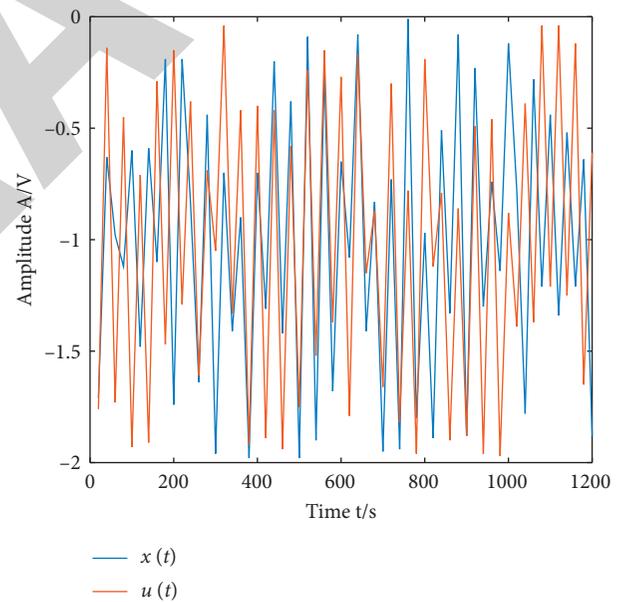


FIGURE 4: Results of stochastic resonance transmission.

does not always reduce or enhance the performance of the neuron model to detect signals. Within a certain noise range, adding noise of appropriate intensity is helpful for information detection and transmission.

**4.3. Weak Digital Pulse Signal Detection.** In this paper, the optimal parameters obtained by KPSO are substituted into the bistable stochastic resonance system, and the test results are shown in Figure 4.

Figure 4 is a time-domain diagram of the stochastic resonance output signal. The comparison shows that the

output of stochastic resonance can better recover the input digital pulse signal, which shows that the adaptive stochastic resonance weak digital pulse signal detection method based on KPSO can effectively detect the weak digital pulse signal.

## 5. Conclusions

In this paper, the basic principle of stochastic resonance is explained through the classic bistable model. Stochastic resonance is explained theoretically from the linear response theory and the adiabatic approximation theory, and the advantages and disadvantages of the two theories are pointed out. This paper also explains the various indicators that currently exist to measure stochastic resonance, proposes the stochastic resonance measure of symbol sequence entropy, and, through experimental analysis, proves the correctness of the system output symbol sequence entropy as the best measure of stochastic resonance, and the use process. Finally, the symbol sequence entropy is used in the fault detection of compressed rolling bearings, which verifies the rationality of the proposed method.

In the real environment, fault diagnosis is based on manual identification, and the influence of human factors will inevitably cause uncertain factors, that is, the inaccuracy and uncertainty of detection. Therefore, combined with stochastic resonance to enhance the fault characteristics, an intelligent detection system is proposed, which uses artificial intelligence algorithms and pattern recognition algorithms to effectively detect the operating status of the machinery, so as to achieve real-time detection and monitoring, and reduce the economic losses caused by mechanical accidents and parking.

In this paper, considering the experimental cost and mature single-chip technology, the adaptive stochastic resonance weak signal detection based on the AVR single-chip microcomputer is realized. For the low-frequency weak signal, the linear search algorithm and the resonance judgment algorithm based on statistical mean and average deviation are implemented. The system can better realize adaptive stochastic resonance detection, but for complex search algorithms or detecting high-frequency weak signals under strong noise background, this system is not competent for the detection task and can be realized by high-end microcontrollers.

## Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

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