

Optimization of Wavelet Threshold based on Sparrow Search Algorithm Integrating Tent Chaos and Cauchy Mutation with Application in Bearing Fault Diagnosis

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Abstract

Wavelet-threshold denoising is strongly affected by the selected threshold when the signal is non-stationary and the noise level is unknown. An overly large threshold may remove impact components, whereas an overly small threshold leaves residual noise after reconstruction. This paper treats threshold selection as an optimization problem and searches it with an improved sparrow search algorithm (ISSA). Tent chaotic mapping is used in the initialization stage to spread candidate thresholds over the search interval. Cauchy mutation is then applied near the current leading position to keep the search from staying too early in a narrow region. Minimum envelope entropy serves as the fitness value, so the search does not require a clean reference signal. The method is tested first on a composite signal containing sinusoidal components and a step term, and then on an outer-ring bearing fault signal. In the simulated signal test, the ISSA-based method increases the signal-to-noise ratio (SNR) by 2.67 dB and reduces the root mean square error (RMSE) by 26.6% compared with the traditional soft-threshold method. In the bearing fault test, the peak SNR of the envelope spectrum increases by 8.3 dB, and fault-related impact information remains visible after denoising.

Keywords

Improved sparrow search algorithm, wavelet threshold denoising, tent chaotic mapping, Cauchy mutation, fault diagnosis.

1. Introduction

Non-stationary signals contain frequency components that change with time, so their useful parts are easily mixed with background noise during measurement [1]. This situation appears in vibration monitoring, biomedical signal analysis, seismic exploration, and related engineering tasks. For rotating machinery, the measured vibration signal may include weak impact components together with broadband noise from the transmission path, sensors, and surrounding equipment. If the noise is not reduced before analysis, later feature extraction and fault diagnosis can be affected. Wavelet transform is often used in this setting because it represents local signal behavior in both the time and frequency domains. Compared with Fourier analysis, which gives a more global frequency description, wavelet analysis is better suited to transients, step changes, and short-duration impacts. This property is consistent with the fault signal considered later in this paper, where the bearing fault is expressed as repeated impact responses.

Hard-threshold and soft-threshold processing are the two basic forms used in wavelet threshold denoising [2]. The hard-threshold function keeps coefficients above the threshold, but the jump at the threshold point may introduce ringing in the reconstructed signal. The soft-threshold function avoids this jump, while its constant shrinkage can also reduce useful signal

amplitude. A further difficulty lies in the threshold value itself. Universal threshold, Stein's unbiased risk estimation, and similar formulas are convenient, but they are preset rules rather than choices made from the measured signal. Their assumptions may be acceptable for some noise models, yet the same threshold can be too conservative or too aggressive when the signal structure changes. When the noise intensity, frequency composition, and time-varying behavior are unknown, a fixed threshold may not match the actual working condition [3].

Adaptive threshold selection can be formulated as an optimization problem, and swarm intelligence algorithms have therefore been introduced into signal processing. The Sparrow Search Algorithm (SSA), proposed by Xue et al. in 2020, models the foraging and anti-predation behavior of sparrow populations. In practical use, SSA is simple to parameterize and can reach a stable solution with a relatively small number of control parameters. Its search process, however, still depends on the initial population distribution. If candidate solutions are concentrated too early, the algorithm may spend many iterations around a local optimum. Existing studies have tried to ease this problem through chaotic initialization, mutation operators, and combined search strategies [4].

The method used in this paper combines tent chaotic mapping, Cauchy mutation, and envelope entropy in the wavelet-threshold search. Tent chaotic mapping is placed before the SSA iteration so that the first group of candidate thresholds covers the search interval more evenly. Cauchy mutation is added around the current leading solution, where occasional larger perturbations can test another part of the threshold interval. Envelope entropy is used to score each candidate threshold without a clean reference signal. The simulation experiment first checks waveform reconstruction and step-edge retention under a controlled signal, including the 50 Hz, 120 Hz, and 200 Hz sinusoidal components and the step term. The bearing fault case [5] then examines whether the denoised signal keeps the impact interval and the BPFO-related components needed for early fault feature extraction.

2. Wavelet Threshold Denoising and the SSA Algorithm

2.1. Principle of Wavelet Threshold Denoising

Discrete Wavelet Transform (DWT) represents a signal through sub-bands with different time and frequency resolutions [6]. For a noisy signal $x(n)=s(n)+\sigma\cdot\epsilon(n)$, $s(n)$ denotes the clean signal, $\epsilon(n)$ denotes zero-mean Gaussian white noise, and σ is the noise standard deviation. Wavelet threshold denoising first decomposes $x(n)$, then modifies selected wavelet coefficients before reconstructing the signal.

After decomposition, the approximation coefficients mainly describe the low-frequency part of the signal, whereas the detail coefficients carry high-frequency components. Noise often appears in the detail coefficients, although useful transient information may also be located there. For this reason, denoising usually processes the detail coefficients with a threshold rather than applying the same operation to all coefficients.

The soft-threshold function is defined as:

$$\hat{d}_j(k)=\begin{cases} \text{sgn}(d_j(k))(|d_j(k)|-\lambda), & |d_j(k)|\geq\lambda \\ 0, & |d_j(k)|<\lambda \end{cases} \quad (1)$$

Where, $d_j(k)$ denotes the wavelet coefficient at the j -th level, λ is the threshold, and $\hat{d}_j(k)$ represents the processed coefficient.

The hard-threshold function is defined as:

$$\hat{d}_j(k) = \begin{cases} d_j(k), & |d_j(k)| \geq \lambda \\ 0, & |d_j(k)| < \lambda \end{cases} \quad (2)$$

The hard-threshold function retains coefficients whose absolute values exceed the threshold. Because the function is discontinuous at the threshold point, oscillation may appear after reconstruction. The soft-threshold function is continuous, but it shrinks each retained coefficient and may reduce the reconstructed amplitude. Traditional denoising often uses the universal threshold λ_{univ} , where n is the signal length. This choice is simple, but it does not include the structure of the measured signal, so the denoising result may vary with signal type.

2.2. Standard SSA

In SSA, the population is divided into discoverers, followers, and vigilantes to imitate the foraging and predator-avoidance behavior of sparrows [7]. Discoverers explore the search space and provide promising directions. Followers move according to the positions found by discoverers and refine the search near better individuals. Vigilantes describe warning behavior; when a dangerous state is detected, they guide the population away from the current region. Through these role updates, SSA alternates between wider exploration and local refinement. Discoverers, tasked with global search, update their positions according to the following formula:

$$X_{i,j}^{t+1} = \begin{cases} X_{i,j}^t \cdot \exp\left(\frac{-i}{\alpha \cdot iter_{max}}\right), & R_2 < ST \\ X_{i,j}^t + Q \cdot L, & R_2 \geq ST \end{cases} \quad (3)$$

where $x_{i,j}$ denotes the position of the i -th sparrow in the j -th dimension at the t -th iteration, $\alpha \in [0,1]$ is a random number, $iter_{max}$ represents the maximum number of iterations, r_2 is the alarm value, st is the safety threshold, q follows a normal distribution, and l is a $1 \times d$ matrix with all elements equal to 1. When $r_2 < st$, the search is treated as safe and the discoverer performs a wider exploration. When $r_2 \geq st$, a warning state is triggered and the discoverer moves quickly to another region.

Followers move with the best-performing individual, and their position update formula is:

$$X_{i,j}^{t+1} = \begin{cases} Q \cdot \exp\left(\frac{X_{worst}^t - X_{ij}^t}{t^2}\right), & i > n/2 \\ X_p^{t+1} + |X_{ij}^t - X_p^{t+1}| \cdot A^+ \cdot L, & i \leq n/2 \end{cases} \quad (4)$$

where x_{worst} denotes the current global worst position, x_p represents the best position currently held by a discoverer, and A^+ is a $1 \times d$ matrix in which each element is randomly assigned as 1 or -1. When $i > n/2$, the follower is regarded as being in a hungry state and searches another region. When $i \leq n/2$, the follower searches near the discoverer.

Vigilantes explore in boundary regions, and their position is updated as follows:

$$X_{ij}^{t+1} = \begin{cases} X_{best}^t + \beta \cdot (X_{ij}^t - X_{best}^t), & f_i > f_g \\ X_{ij}^t + K \cdot \left(\frac{X_{ij}^t - X_{worst}^t}{(f_i - f_w) + \epsilon}\right), & f_i = f_g \end{cases} \quad (5)$$

where x_{best} is the current global optimum position, β is a step-size control parameter following a normal distribution with mean 0 and variance 1, f_i is the fitness value of the i -th sparrow, f_g and f_w are the current global best and worst fitness values, $k \in [-1,1]$ is a random number, and ϵ is a small constant used to avoid division by zero.

3. ISSA

3.1. Tent Chaotic Mapping Initialization

The standard SSA usually starts from randomly generated individuals. For threshold search, this may leave some parts of the interval under-sampled and cause several candidates to gather in a local region at the first iteration. Once this happens, later position updates tend to be affected by the early distribution of candidates. Chaotic mapping offers a deterministic way to generate a sequence with irregular but bounded movement. Among common chaotic maps, the tent map is simple and has relatively uniform traversal behavior [8]. Its iterative formula is defined as:

$$x_{n+1} = \begin{cases} 2x_n, & x_n < 0.5 \\ 2(1-x_n), & x_n \geq 0.5 \end{cases} \quad (6)$$

Where, $x_n \in (0,1)$. The Lyapunov exponent of the tent mapping is $\ln 2 > 0$, indicating that the system is in a chaotic state. Compared with the logistic map, the tent map possesses better ergodic uniformity and faster iteration speed.

The initial population is generated using the tent mapping as follows:

$$X = \lambda_{\min} + x \cdot (\lambda_{\max} - \lambda_{\min}) \quad (7)$$

where x is the chaotic sequence produced by the tent mapping, and $[\lambda_{\min}, \lambda_{\max}]$ denotes the search interval. In this step, the chaotic sequence is mapped into the threshold range, so the first population covers the interval more evenly than a purely random draw. This gives the subsequent SSA update a broader set of candidate thresholds at the beginning of the search.

3.2. Cauchy Mutation Strategy

When the current best individual is close to a local optimum, the SSA update may generate only small changes around that position. To keep the search from becoming too concentrated, a Cauchy mutation operator [9] is added at the global best position. The probability density function of the Cauchy distribution is:

$$f(x) = \frac{1}{\pi} \cdot \frac{\gamma}{\gamma^2 + (x - x_0)^2} \quad (8)$$

Where, x_0 is the location parameter and γ is the scale parameter. For the standard Cauchy distribution, $x_0 = 0$ and $\gamma = 1$.

The heavy tail of the Cauchy distribution means that most perturbations remain near the current position, while a small number of perturbations can be much larger. This property is useful when the search has already gathered around the present best solution. Compared with Gaussian perturbation, Cauchy mutation has a higher probability of producing a candidate

farther from the current point, which gives the algorithm a chance to test another part of the threshold interval.

The Cauchy mutation is applied to the global best position as follows:

$$X = x_{\text{best}} + \delta \cdot \text{cauchy}(0, 1) \quad (9)$$

Δ is the mutation step size, employing an adaptive strategy:

$$\delta = \delta_0 \cdot \left(1 - \frac{t}{\text{iter}_{\text{max}}}\right) \quad (10)$$

where δ_0 is the initial step size. As the iteration number increases, δ becomes smaller. Thus, the mutation range is wider in the early iterations and becomes more conservative near the end of the search.

3.3. Envelope Entropy Fitness Function

In many engineering measurements, the clean signal is unavailable, so SNR or RMSE cannot be used directly as the search objective. This paper therefore uses envelope entropy as the fitness function [10]. Envelope entropy describes the dispersion of the signal envelope: impulsive components tend to make the envelope energy more concentrated, while noise-dominated signals usually produce a more dispersed envelope. The definition of envelope entropy is:

$$H_e = - \sum_{i=1}^N p_i \ln p_i, \quad p_i = \frac{a_i}{\sum_{j=1}^N a_j} \quad (11)$$

where a_i is the amplitude of the envelope signal obtained by Hilbert transform. A smaller envelope entropy value means that the impact components are more concentrated in the envelope and the denoised signal contains clearer impulse features. Because this criterion is calculated from the measured signal itself, the threshold search does not require a clean reference signal.

3.4. ISSA Algorithm Procedure

Algorithm 1 summarizes the ISSA procedure used for wavelet-threshold optimization. The population is first initialized by tent chaotic mapping. In each iteration, individuals are ranked by envelope entropy, the positions of discoverers, followers, and vigilantes are updated, and the Cauchy mutation is then applied to the current best position. The threshold with the minimum envelope entropy is finally used in the wavelet denoising step.

Algorithm 1: ISSA for Wavelet Threshold Optimization

1. Input: Noisy signal $x(n)$, wavelet basis sym8 , decomposition level $j=5$; Output: Optimal threshold λ^*
2. Initialization: $N_p=30$, $t_{\text{max}}=50$, $[\lambda_{\text{min}}, \lambda_{\text{max}}]=[0.1, 3.0]$
3. Initialize the population x using tent chaotic mapping. Calculate the initial fitness $h_e(x_i)$ for each individual and record x_{best}
4. **For** $t=1$ to t_{max} **do**

5. Rank individuals by fitness. Update the positions of the discoverers (top 20%), followers (remaining 80%), and vigilants (random 20%)
 6. Apply Cauchy mutation to x_{best} : $X = x_{best} + \delta \cdot \text{cauchy}(0,1)$
 7. Perform boundary handling, calculate the new fitness, and update x_{best} and f_{best}
 8. End for
 9. Apply the optimal threshold $\lambda^* = x_{best}$ to perform wavelet denoising on $x(n)$, obtaining (n)
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The main computational cost comes from fitness evaluation. In one iteration, the algorithm evaluates np individuals, and each evaluation includes wavelet decomposition, coefficient thresholding, wavelet reconstruction, and envelope entropy calculation. If the signal length is n , one evaluation has a time complexity of $O(n \log n)$. The overall time complexity is therefore $O(t_{max} \cdot np \cdot n \log n)$. When the implementation environment allows it, the fitness evaluations of different individuals can be computed in parallel.

4. Experimental Design and Result Analysis

4.1. Simulation Signal Experiment

A composite non-stationary signal is constructed to test how the ISSA-based threshold handles multi-frequency components and an abrupt step:

$$S(t) = \sin(2\pi \cdot 50t) + 0.5 \sin(2\pi \cdot 120t) + S_{step}(t) + 0.3 \sin(2\pi \cdot 200t) \quad (12)$$

The signal contains three sinusoidal components at 50 Hz, 120 Hz, and 200 Hz, together with a step term $s_{step}(t)$. The three frequencies are used to observe whether the denoising method preserves components at different bands. The step term is included to check edge retention after thresholding. The component amplitudes are not the same, so the reconstructed signal also reflects whether lower-energy details are weakened during denoising.

Gaussian white noise with a standard deviation of $\sigma=0.5$ was added to the composite signal, giving an input SNR of 3.01 dB. The sampling frequency was 1024 Hz, and the signal length was 1025 points. The sym8 wavelet was used for 5-level decomposition because its symmetry and regularity are suitable for signals that contain abrupt changes.

In Figure 1, the noisy composite signal has large amplitude fluctuation, and the step edge is difficult to locate directly. After hard-threshold processing, part of the noise is removed, but oscillation appears near the step transition. The oscillation lasts about ± 0.02 s around the transition point and has an amplitude of about ± 0.15 , which is related to the discontinuity of the hard-threshold function. These oscillations do not belong to the constructed clean signal, so they may be confused with high-frequency details if the denoised waveform is used directly. Soft-threshold processing reduces this ringing, but the waveform around the step is also weakened; the rising and falling edges become flatter, and the rise time increases to about 0.025 s. With the ISSA-based threshold, the transition remains visible and the rise time is about 0.015 s, which is closer to the original value of 0.012 s. The sinusoidal components can still be recognized after reconstruction, especially in the parts away from the step transition.

The enlarged step-edge region in Figure 2 makes the difference between the three denoising results easier to see. Around the transition point, the hard-threshold result contains high-frequency oscillations for approximately 0.02 s. The soft-threshold result removes most of this oscillation, but the edge becomes blurred and the slope of the rising edge decreases. In the ISSA result, the transition region is closer to the original signal, and the rise time is the nearest among the three processed signals.

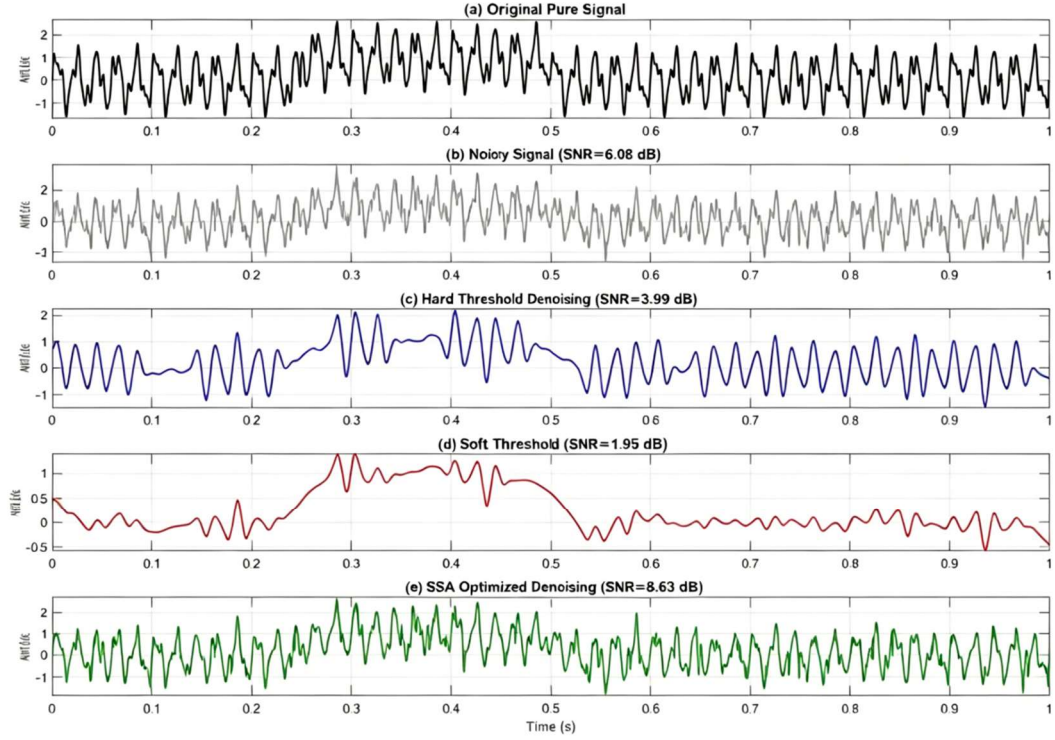


Figure 1. Time-domain Denoising Results Comparison of the Three Methods

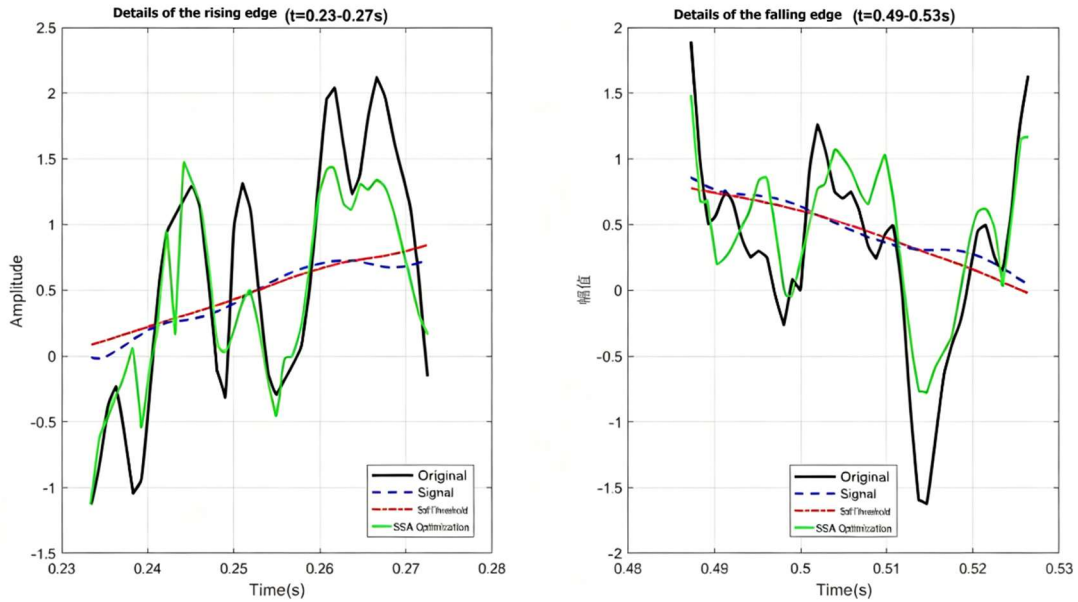


Figure 2. Comparison of Local Step-edge Details

The numerical comparison in Table 1 is consistent with the visual results. The SNR obtained by ISSA is 13.12 dB. It is 10.11 dB higher than the noisy signal, 3.25 dB higher than the hard-threshold result, and 2.67 dB higher than the soft-threshold result. The corresponding SNR increases over the hard-threshold and soft-threshold methods are 32.9% and 25.5%. The RMSE of ISSA is 0.2201, which is 0.0800 lower than the soft-threshold result and corresponds to a 26.6% reduction. The MAE is 0.1678, and the correlation coefficient is 0.9456. The SNR change

reflects the reduction of background noise, while the RMSE and correlation coefficient correspond to the closeness between the denoised waveform and the original signal. These values match the waveform in Figure 1, where the noise is reduced while the edge and sinusoidal components are still retained.

Table 1. Performance Comparison of the Three Denoising Methods

Method	SNR(dB)	RMSE	MAE	Correlation Coefficient
Noisy Signal	3.01	0.5000	0.3989	0.7234
Hard Threshold	9.87	0.3214	0.2456	0.8912
Soft Threshold	10.45	0.3001	0.2301	0.9045
ISSA	13.12	0.2201	0.1678	0.9456

Figure 3 shows the convergence curve of ISSA. From iterations 1 to 20, the fitness changes from -8.5 dB to -12.3 dB, a change of 3.8 dB. This early drop is related to the wider initial distribution produced by tent chaotic mapping, which gives the discoverers more candidate regions to search. Between iterations 21 and 40, the curve changes more slowly, from -12.3 dB to -13.08 dB, while followers and vigilantes refine the search and Cauchy mutation is still used to test nearby alternatives. After iteration 40, the fitness fluctuates around -13.12 dB, and the fluctuation is less than 0.05 dB. The final threshold stabilizes at $\lambda^*=1.87$, lower than the universal threshold of 2.34, suggesting that the conventional threshold may remove too much useful signal energy in this example.

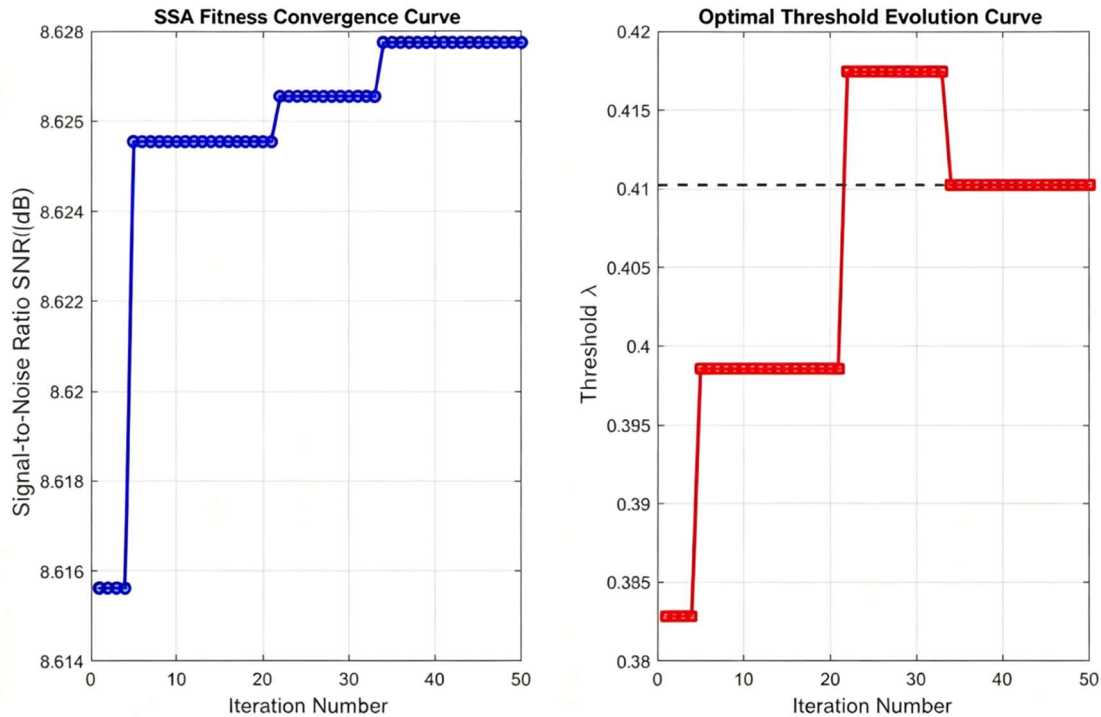


Figure 3. ISSA Algorithm Convergence Characteristics Analysis

The bar chart in Figure 4 places the four metrics side by side. Among the three methods, ISSA gives the highest SNR, with increases of 32.9% and 25.5% over the hard-threshold and soft-threshold methods. Its RMSE and MAE are lower than those of the two traditional thresholding methods, and its correlation coefficient is closer to 1. The four bars therefore point to the same

reading of the experiment: the optimized threshold does not only smooth the noisy signal, but also keeps the reconstructed waveform closer to the original signal. This agrees with the edge behavior shown in Figures 1 and 2.

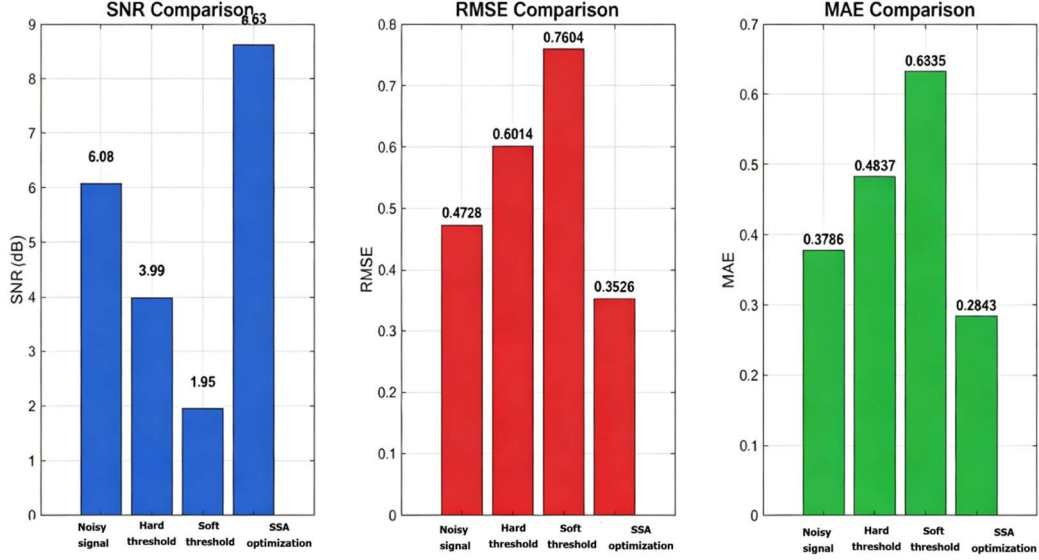


Figure 4. Comparison of Quantitative Indicators for the Three Methods

4.2. Bearing Fault Diagnosis Experiment

A rolling-bearing outer-race fault case is used to examine whether the denoising method is useful for fault feature extraction [9]. In rotating machinery, an outer-race defect generates periodic impact vibration, but the impact component is often weak compared with background noise and other vibration components. If the impacts are covered before envelope analysis, the characteristic frequency may be difficult to identify. For this reason, the bearing signal is denoised before the frequency-domain diagnosis step.

Simulated bearing parameters are as follows. The outer race fault characteristic frequency Ball Pass Frequency Outer (BPFO)=107 Hz, the rotational frequency is 30 Hz, and the bearing's natural frequency is 3000 Hz. The BPFO is calculated using the formula:

$$f_{BPFO} = \frac{n}{2} f_r \left(1 - \frac{d}{D} \cos \alpha \right) \quad (13)$$

where n is the number of rolling elements, f_r is the rotational frequency, d is the ball diameter, D is the pitch diameter, and α is the contact angle. With the parameters used in this study, BPFO is calculated as 107 Hz.

The fault impulse is modeled as a decaying oscillation:

$$X_{\text{impact}}(t) = 1.5 \cdot e^{-0.05 \cdot 2\pi \cdot 3000t} \cdot \sin(2\pi \cdot 3000t) \quad (14)$$

Here, the damping ratio is 0.05, and 3000 Hz is the natural frequency of the bearing. The decaying oscillation term is used to approximate the impact response produced by a bearing fault.

For the bearing fault signal in Figure 5, the clean waveform contains periodic impacts with an interval of about 9.3 ms, corresponding to the outer-race fault frequency of 107 Hz. Each impact is followed by a decaying oscillation whose amplitude gradually returns toward zero. After

noise is added, the impact positions are partly covered by background fluctuation, and some local peaks no longer correspond clearly to the fault impulses. The hard-threshold and soft-threshold results recover some impact traces, but residual noise and amplitude attenuation remain in both waveforms. In the displayed ISSA result, adjacent impacts are easier to separate, and the interval pattern is still visible after denoising. This provides a more stable input for the following envelope-spectrum analysis, where the BPFO peak and its harmonics are used for diagnosis.

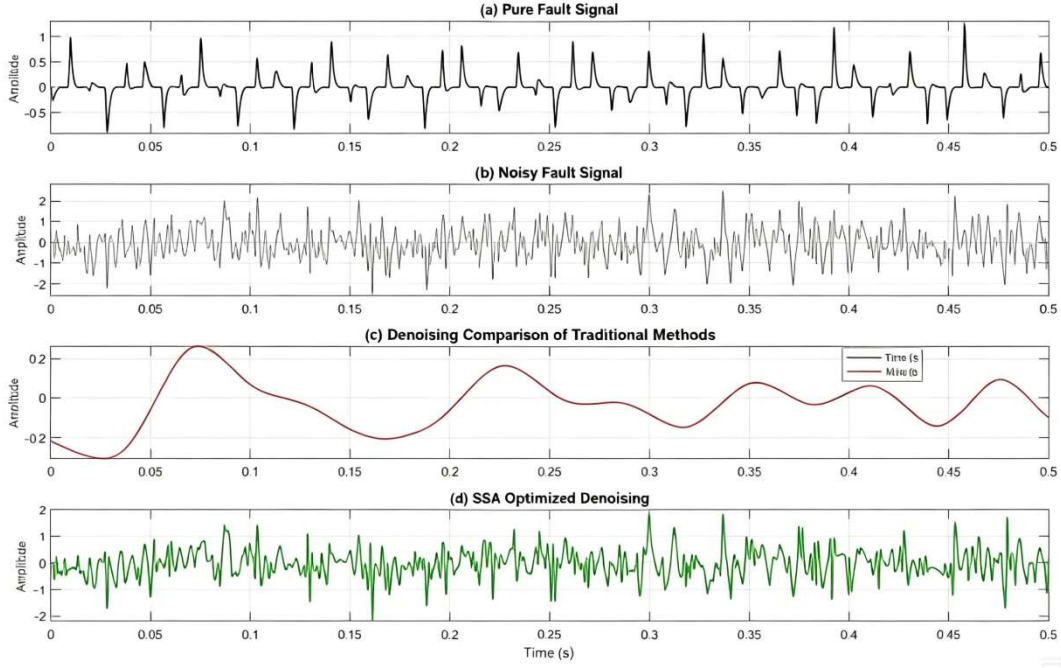


Figure 5. Comparison of Denoising Effects on the Bearing Fault Signal

The time-domain comparison suggests that the ISSA result retains more impact amplitude after noise reduction. The next step is to check whether this improvement also appears in the frequency-domain fault features. In envelope spectrum analysis, the signal envelope is first obtained by Hilbert transform, and FFT is then applied to the envelope. The visibility of BPFO and its harmonics in the envelope spectrum is used here to judge the feature extraction result after denoising.

The envelope spectra of the three denoising methods show different feature-retention behavior. The hard-threshold result keeps part of the fault information, but the noise floor is still high and the feature peaks are not distinct. The soft-threshold result suppresses more noise, while the harmonic components become weaker. The ISSA result gives a lower background level and clearer peaks at the fault-related frequencies, which makes the BPFO components easier to read from the spectrum.

The envelope spectra in Figure 6 show the difference after denoising. For the hard-threshold result, the SNR of BPFO at 107 Hz is 12.5 dB, and the harmonic components are weak. The soft-threshold result raises the BPFO SNR to 15.8 dB, but the harmonic peaks are still close to the background. After ISSA processing, the BPFO peak at 107 Hz reaches 24.1 dB, which is 8.3 dB higher than the soft-threshold result. The peak amplitude is 12.2 times the noise baseline. The harmonic amplitudes at 214 Hz and 321 Hz are 0.0198 and 0.0124, respectively. In this experiment, the fundamental frequency and its two harmonics can be read from the same spectrum. This is more convincing than relying on a single isolated peak, because the 214 Hz and 321 Hz components follow the expected multiples of 107 Hz.

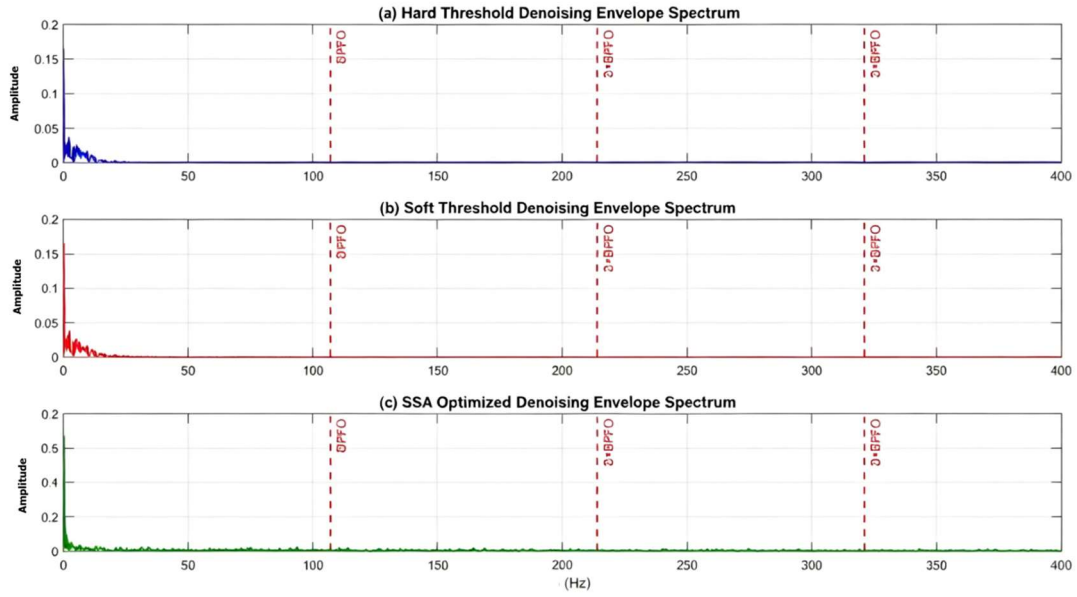


Figure 6. Comparison of Envelope Spectrum Analysis

5. Conclusion

This study uses ISSA to search the wavelet threshold for non-stationary signal denoising. The search combines tent chaotic mapping, Cauchy mutation, and envelope entropy, and the method is tested with a simulated signal and a bearing fault signal. The experiments mainly examine two points: waveform reconstruction with transient information, and fault-frequency readability after denoising. The controlled simulation gives a reference for checking the edge and sinusoidal components, while the bearing signal gives a diagnostic case with periodic impacts under noisy simulated conditions.

(1) Tent chaotic mapping is used before the SSA iteration to distribute candidate thresholds across the search interval. Cauchy mutation is used during the search stage and adds occasional larger perturbations near the current leading position. In the convergence curve, the fitness decreases rapidly in the early iterations and becomes stable after about 40 iterations, which is consistent with the intended role of these two operations.

(2) Envelope entropy is used as the fitness function because it is calculated from the measured signal itself. Under this setting, the threshold search does not need a clean reference signal. The fitness value is obtained after wavelet reconstruction and envelope extraction for each candidate threshold. This is why the same criterion can be used in both the simulated signal and the bearing fault signal.

(3) In the simulated signal experiment, the ISSA method obtains an SNR of 13.12 dB, which is 2.67 dB higher than the soft-threshold result. The RMSE is reduced by 26.6%, the MAE value is 0.1678, and the correlation coefficient is 0.9456. The convergence curve reaches a stable value after about 40 iterations, with the final threshold around $\lambda^*=1.87$. This threshold is lower than the universal threshold of 2.34 in the same experiment, which explains why the reconstructed signal keeps more edge information.

(4) For the bearing fault signal, ISSA increases the SNR of the envelope-spectrum peak by 8.3 dB and gives a peak-to-valley ratio of 12.2. The frequency-multiplication components at 214 Hz and 321 Hz remain distinguishable after denoising. Together with the visible impact intervals in the time-domain waveform, the envelope-spectrum result supports the use of the denoised signal for weak fault feature extraction. The conclusion is limited only to the simulated bearing setting and parameter values used in this experiment.

The present work still uses a fixed wavelet basis and a limited set of test signals. Later studies can combine ISSA with variational mode decomposition for more complex operating conditions, and can also examine adaptive wavelet-basis selection for different signal types. Additional diagnosis cases, such as gear faults and rotor imbalance, would help check whether the same threshold-search strategy works when the impact pattern or frequency distribution changes. Real-time implementation is another issue, especially when the denoising step must be completed before online diagnosis.

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