Signal Denoising Algorithm Based on Bee Colony Algorithm and New Threshold Function (Postprint)

Authors: Deng Gaofeng, Ye Jincai, Wang Guofu, Faquan Zhang

Date: 2018-07-09T00:00:00+00:00

Abstract

To address the problem of parameter value selection for thresholds and threshold functions, a signal denoising algorithm based on a new parameterized threshold function using the Artificial Bee Colony optimization algorithm is proposed. First, the continuity, high-order differentiability, and parameter tunability of the new parameterized threshold function are verified. Second, according to the minimum mean square error (MSE) strategy, the Artificial Bee Colony optimization algorithm is employed to optimize the thresholds and tuning parameters at each decomposition level to obtain the optimal denoised signal. Finally, the signal-to-noise ratio (SNR) and MSE metrics are utilized to verify the denoising effectiveness of the signal. Experimental results demonstrate that the threshold parameters selected by the Artificial Bee Colony optimization algorithm and the new wavelet threshold function can effectively denoise noisy signals.

Full Text

Preamble

Title: Signal Denoising Method Based on Bee Colony Algorithm and New Threshold Function

Authors: Deng Gaofeng, Ye Jincai†, Wang Guofu, Zhang Faquan
(School of Information & Communication, Guilin University of Electronic Technology, Guilin, Guangxi 541004, China)

Abstract: Addressing the challenges of selecting adjustment parameters for thresholds and threshold functions, this paper proposes a signal denoising algorithm based on an artificial bee colony optimization algorithm with a parameterized new threshold function. First, the continuity, high-order differentiability, and parameter adjustability of the new threshold function are theoretically verified. Second, according to the minimum mean square error (MSE) strategy, the artificial bee colony optimization algorithm is employed to optimize the thresholds and adjustment parameters across all decomposition layers, yielding the optimal denoised signal. Finally, the denoising performance is evaluated using signal-to-noise ratio (SNR) and MSE metrics. Experimental results demonstrate that the threshold parameters selected by the artificial bee colony optimization algorithm, combined with the new wavelet threshold function, can effectively denoise noisy signals.

Keywords: wavelet analysis; artificial bee colony algorithm; adjustment parameters; threshold function; signal denoising

0 Introduction

Signal denoising is a fundamental technique in signal processing aimed at maximizing the recovery of the original signal, representing a critical component of signal processing. Traditional denoising methods typically rely on Fourier transforms. Over the past decade, the importance of wavelet transforms in time-frequency signal analysis has grown with the increasing significance of multi-resolution analysis and local signal feature analysis. Wavelet transform in signal processing involves partial transformation in both spatial and frequency domains. The process of accurately extracting effective signals from noisy signals is termed signal denoising. The selection of threshold functions and thresholds determines the effectiveness of wavelet threshold denoising.

The choice of threshold function is a key factor affecting wavelet denoising performance. As the most fundamental threshold functions, both hard and soft threshold methods have inherent defects. The hard threshold function suffers from discontinuity at break points, while the soft threshold function exhibits a constant bias problem. To overcome these limitations, the sigmoid threshold function was proposed in 2012 [2]. Although this function provides better quantization effects for wavelet coefficients, there remains room for further improvement in wavelet coefficient quantization. Therefore, this paper proposes a differentiable threshold function based on a cosine function, which enhances the flexibility of the threshold function by introducing adjustment factors. Threshold selection is another critical element determining wavelet denoising effectiveness. In wavelet decomposition coefficients, the wavelet coefficients corresponding to the original signal are significantly larger than those of noise [3]. Thus, selecting an appropriate threshold can effectively filter out noise coefficients from the wavelet coefficients. Previous threshold determination methods mainly include adaptive thresholding based on neighborhood windows and empirical threshold selection. The former estimates reasonable thresholds by exploiting the correlation of neighboring wavelet coefficients within each decomposition layer [4], while the latter relies on repeated experiments and empirical selection, requiring substantial workload. To overcome the drawbacks of manual iterative parameter tuning and to obtain optimal thresholds, this paper employs swarm intelligence optimization techniques to acquire reasonable thresholds and adjustment parameters, such as particle swarm optimization, ant colony algorithms, and artificial fish swarm algorithms. Given that the artificial bee colony algorithm exhibits good convergence properties [5], is suitable for multi-variable optimization problems [6], and possesses strong global search capabilities [7][8], this paper adopts the artificial bee colony algorithm to optimize thresholds and adjustment parameters, combining it with a parameterized threshold function to achieve effective filtering of noisy signals.

1 Wavelet Threshold Function Design

Wavelet thresholding includes hard and soft threshold methods, both of which operate based on a specific threshold as a 分界点. The difference lies in their treatment of coefficients across different scale spaces: the hard threshold function sets decomposition coefficients with absolute values smaller than the threshold to zero while retaining those with absolute values larger than the threshold [9]. The hard threshold function is defined as:

$$\hat{d}_{k,j} = \begin{cases} 0, & |d_{k,j}| < \lambda \\ d_{k,j}, & |d_{k,j}| \geq \lambda \end{cases}$$

The soft threshold function sets coefficients with absolute values smaller than the threshold to zero, while for those larger than the threshold, it removes the noise component carried by the coefficient through a specific algorithm. The soft threshold function is defined as:

$$\hat{d}_{k,j} = \begin{cases} 0, & |d_{k,j}| < \lambda \\ \operatorname{sgn}(d_{k,j})(|d_{k,j}| - \lambda), & |d_{k,j}| \geq \lambda \end{cases}$$

To overcome the defects of hard and soft threshold functions, this paper proposes a new wavelet threshold function based on a cosine function:

$$\hat{d}_{k,j} = \begin{cases} 0, & |d_{k,j}| < \lambda \\ \operatorname{sgn}(d_{k,j}) \left[\lambda + \frac{\lambda}{\pi} \exp\left(1 - \frac{d_{k,j}^2}{\lambda^2}\right) \cos\left(\frac{\pi d_{k,j}}{2\lambda}\right) \right], & |d_{k,j}| \geq \lambda \end{cases}$$

where $d_{k,j}$ represents the wavelet coefficient, λ is the threshold, and α is the adjustment factor. By freely adjusting the value of α, the threshold function can better adapt to noisy signals with different characteristics. Clearly, the new threshold function is composed of exponential and trigonometric components. Based on the properties of elementary functions, the new threshold function also possesses continuity and high-order differentiability. Consequently, it can overcome the pseudo-Gibbs phenomenon caused by discontinuity and effectively suppress oscillations, resulting in smoother reconstructed denoised signals.

To directly observe the characteristics of the new threshold function and the effect of the adjustment parameter, we simply set $\lambda = 4$ and compare the graphs of different threshold functions and the new threshold function with different α values, as shown in [Figure 1: see original paper]. In the figure, H-T denotes the hard threshold function, S-T denotes the soft threshold function, N-T denotes the new threshold function, and the numbers 2, 10, and 20 represent different values of α. The figure clearly shows that as α becomes smaller, the new threshold function exhibits characteristics similar to the soft threshold function, while as α increases, it approaches the hard threshold function. This demonstrates that the new threshold function is a flexible soft-hard threshold function that can be freely adjusted through the parameter α.

---

2 Artificial Bee Colony Algorithm (ABC)

The ABC algorithm is a heuristic optimization algorithm based on iterative principles, inspired by the foraging behavior of honeybee swarms [10]. Standard artificial bees are divided into three types: employed bees, onlooker bees, and scout bees. Employed bees search all food sources and explore regions rich in nectar, sharing information through behavioral communication among bees, allowing food sources to be exploited by onlooker and scout bees to select the optimal nectar source. The ABC algorithm primarily consists of four steps: initialization of the swarm, employed bee phase, onlooker bee phase, and scout bee phase [11].

2.1 Swarm Initialization

The food sources (employed bees) with SN individuals and D dimensions are generated using a random function. The food source generation formula is as follows:

$$x_{i,j} = x_{\min,j} + \text{rand}(0,1) \times (x_{\max,j} - x_{\min,j})$$

where $i = 1, 2, 3, \ldots, SN$ represents the number of food sources, $j = 1, 2, 3, \ldots, n$ represents each dimension of the food source, and $x_{\min,j}$ and $x_{\max,j}$ represent the minimum and maximum values in the j-dimensional space, respectively.

2.2 Employed Bee Phase

Employed bees search the neighborhood of each nectar source and calculate the fitness value of each food source to share with onlooker bees. The search formula is:

$$v_{i,j} = x_{i,j} + \varphi_{i,j} \times (x_{i,j} - x_{r,j})$$

where $r \in \{1, 2, \dots, SN\}$ and $r \neq i$, and $\varphi_{i,j}$ is a random number in the range $[-1, 1]$. Through greedy selection, the better nectar source is chosen between x_i and v_i. The fitness value of a nectar source is calculated as:

$$\text{fitness}_i = \begin{cases} \frac{1}{1+F_i}, & F_i \geq 0 \\ 1 + |F_i|, & F_i < 0 \end{cases}$$

where F_i is the objective function value of the solution.

2.3 Onlooker Bee Phase

Onlooker bees select optimal food sources based on probability evaluations related to nectar abundance. This probability evaluation formula is:

$$P_i = \frac{\text{fitness}_i}{\sum_{n=1}^{SN} \text{fitness}_n}$$

where fitness_i is the fitness value of the i-th food source. The richness of nectar is proportional to its probability of being selected. Food sources with larger probability estimates are chosen using a roulette wheel selection scheme.

2.4 Scout Bee Phase

If a food source x_i does not improve within a predetermined cycle, it is abandoned. The scout bee becomes an employed bee and generates a new food source randomly in the current maximum region using formula (3-2).

---

3 Objective Function and Algorithm Flow

3.1 Objective Function

The primary metrics for evaluating denoised signal quality are the signal-to-noise ratio (SNR) and mean square error (MSE) between the reconstructed signal and the original signal [12], defined as follows:

$$\text{SNR} = 10 \log_{10} \frac{\sum_{n=1}^{N} X[n]^2}{\sum_{n=1}^{N} (X[n] - \hat{X}[n])^2}$$

$$\text{MSE} = \frac{1}{N} \sum_{n=1}^{N} (X[n] - \hat{X}[n])^2$$

where $X[n]$ is the original signal and $\hat{X}[n]$ is the denoised signal. Using formula (4-2) as the objective function for formula (3-3), we construct the fitness function for the proposed algorithm.

3.2 Denoising Parameter Settings and Algorithm Flow

The denoising algorithm consists of three steps: (a) Apply stationary wavelet transform (SWT) technology [13] to decompose the noisy signal into characteristic coefficients and detail coefficients; (b) Use the thresholds and adjustment parameters of each decomposition layer as coordinate components of the solution, and employ the ABC algorithm to optimize these thresholds and parameters, outputting the optimal threshold and adjustment parameters; (c) Perform signal denoising using the optimal thresholds and adjustment parameters for each decomposition layer, outputting the denoised signal. The denoising algorithm flowchart is shown in [Figure 2: see original paper].

---

4 Experimental Results and Analysis

4.1 Denoising Parameter Settings

Wavelet parameters: After extensive comparison of experimental results using different filters and decomposition levels, this experiment sets the decomposition level to 4 and uses the Haar filter.

ABC parameters: The solution dimension is determined as the sum of the number of decomposition layers and adjustment parameters, i.e., $D = 5$. The number of iterations is 50. The threshold interval for each decomposition layer is $[0, 100]$. Based on [Figure 1: see original paper], the adjustment parameter interval is set to $[0, 50]$. The number of food sources SN is 10. The limit for unupdated optimal solutions is $0.5 \times SN \times D = 25$.

4.2 Experimental Results Analysis

To verify the effectiveness and universality of the proposed algorithm, Bumps and Blocks benchmark signals are selected as test signals. Gaussian white noise of different intensities is added to these benchmark signals to generate noisy signals with SNR values of 10 dB and 15 dB. Using MSE and SNR as denoising performance indicators, the denoising effects of hard, soft, Sigmoid threshold functions, and the new threshold function are compared. The denoising data are presented in . [Figure 3: see original paper] shows the convergence curves of the ABC algorithm. [Figure 4: see original paper] displays the denoised Bumps signals at SNR = 10 dB and 15 dB, while [Figure 5: see original paper] shows the denoised Blocks signals at the same SNR levels.

The data in indicate that both Sigmoid and the new threshold function outperform hard and soft threshold functions in denoising metrics. However, the new threshold function achieves higher SNR and lower MSE, demonstrating superior denoising performance for the signals considered in this paper. In [Figure 3: see original paper], the vertical axis represents MSE and the horizontal axis represents iteration number. The four subplots clearly show that as the number of iterations increases, the algorithm continuously optimizes the thresholds and adjustment parameters to achieve smaller MSE, with particularly fast convergence in the early to middle stages. [Figure 4: see original paper] and [Figure 5: see original paper] clearly display the signals denoised by different threshold functions. Taking [Figure 4: see original paper] as an example, the soft threshold function produces the worst visual denoising effect. The hard threshold function still retains significant noise, whereas the new threshold function demonstrates overall superior denoising performance compared to the Sigmoid threshold function.

---

5 Conclusion

This paper proposes a signal denoising algorithm based on the ABC algorithm with a parameterized new threshold function. Through theoretical proof and simulation analysis, the following conclusions can be drawn:

a) A novel parameterized threshold function is proposed for wavelet threshold denoising of noisy signals. This threshold function exhibits continuity, high-order differentiability, and parameter adjustability across its entire domain. Data analysis demonstrates that the threshold function can effectively quantify wavelet coefficients and achieve satisfactory denoising performance.

b) This paper combines the wavelet threshold function with the ABC algorithm to propose a novel denoising method. Using thresholds and adjustment parameters as coordinates of solutions in the ABC algorithm and minimizing the MSE between the original and reconstructed signals, optimal thresholds and adjustment parameters can be obtained quickly and efficiently. This method possesses adaptive characteristics that overcome the inflexibility of traditional threshold denoising methods.

References

[1] Donoho D L. De-noising by soft-thresholding [M]. [S. l.]: IEEE Press, 1995.

[2] Yi Tinghua, Li Hongnan, Zhao Xiaoyan. Noise smoothing for structural vibration test signals using an improved wavelet thresholding technique [J]. Sensors, 2012, 12 (8): 11205.

[3] Wu Guangwen, Wang Changming, Bao Jiandong, et al. A wavelet threshold de-noising algorithm based on adaptive threshold function [J]. Journal of Electronics & Information Technology, 2014, 36 (6): 1340-1347.

[4] Gao Guorong, Liu Yanping, Pan Qiong. A differentiable thresholding function and an adaptive threshold selection technique for pulsar signal denoising [J]. Acta Physica Sinica, 2012, 61 (13): 549-553.

[5] Ning Aiping, Zhang Xueying. Convergence analysis of artificial bee colony algorithm [J]. Control & Decision, 2013 (10): 1554-1558.

[6] Karaboga D, Gorkemli B, Ozturk C, et al. A comprehensive survey: artificial bee colony (ABC) algorithm and applications [J]. Artificial Intelligence Review, 2014, 42 (1): 21-57.

[7] He Yao, Liu Jianhua, Yang Ronghua. Research on Artificial Bee Colony Algorithm [J]. Application Research of Computers, 2018, 35 (5): 1281-1286.

[8] Zhao Hui, Li Mudong, Weng Xingwei. Improved artificial bee colony algorithm with self-adaptive global best-guided quick searching strategy [J]. Control & Decision, 2014 (11): 2041-2047.

[9] Lu Jingyi, Lin Hong, Ye Dong, et al. A New Wavelet Threshold Function and Denoising Application [J]. Mathematical Problems in Engineering, 2016, (2016-5-9), 2016, 2016 (3): 1-8.

[10] Karaboga D, Basturk B. A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm [M]. Kluwer Academic Publishers, 2007.

[11] Sheng Xiajiong, Wang Long, Han Daojun. Application of BP neural network optimized by artificial bee colony in intrusion detection [J]. Computer Engineering, 2016, 42 (2): 190-194.

[12] Yang Yuefeng, Liu Hui, Tan Jianping. Research on wavelet-based speech signal with noise denoising algorithms [J]. Computer Engineering and Applications, 2015, 51 (14): 211-213.

[13] Zhong Shuncong, Oyadiji, S. Olutunde. Crack detection in simply supported beams using stationary wavelet transform of modal data [J]. Structural Control & Health Monitoring, 2015, 18 (2): 169-190.

Note: Figure translations are in progress. See original paper for figures.

Source: ChinaXiv —Machine translation. Verify with original.