Postprint of Research on Improved PF Algorithm for Denoising AE Signals in Coal and Gas Outbursts

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Abstract

Coal and gas outbursts generate acoustic emission (AE) signals. To address the problem of extracting relatively pure and effective AE signals, a denoising method is proposed that intelligently optimizes particle filter (PF) using a dynamically neighborhood-adjusted (D) fruit fly algorithm (FOA). This method utilizes fruit fly individuals to represent each signal point particle in PF, optimizes the resampling process of the particle filter, and improves the optimization capability and convergence speed of the fruit fly algorithm by dynamically adjusting the number of neighborhood particles. Using root mean square error and signal-to-noise ratio as evaluation metrics, the AE signals of coal and gas outbursts obtained by the signal acquisition system were denoised using standard particle filter, fruit fly optimized particle filter, and improved particle filter, respectively. The results show that the signal-to-noise ratio of the improved particle filter method increased by approximately 15.3 dB, and its root mean square error was the lowest. Compared with the other two methods, the improved particle filter achieved the optimal denoising effect.

Full Text

Research on Denoising of AE Signals from Coal-Gas Outbursts Using Improved PF Algorithm

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Abstract: Coal-gas outbursts produce acoustic emission (AE) signals. To address the challenge of extracting pure and effective AE signals, this paper proposes an intelligent optimized particle filter (PF) denoising method based on a fruit fly algorithm (FOA) with dynamic neighborhood adjustment (D). The method utilizes fruit fly individuals to represent each signal point particle in PF, optimizes the resampling process of particle filtering, and improves the optimization capability and convergence speed of the fruit fly algorithm by dynamically adjusting the number of neighborhood particles. Using root-mean-square error and signal-to-noise ratio as evaluation metrics, the AE signals of coal-gas outbursts obtained from a signal acquisition system were denoised using standard particle filtering, fruit fly optimized particle filtering, and improved particle filtering. The results demonstrate that the improved particle filtering method enhances the signal-to-noise ratio by approximately 15.3 dB and achieves the lowest root-mean-square error. Compared with the other two methods, the improved particle filter yields the optimal denoising effect.

Keywords: coal-gas outbursts; AE signal; denoising; particle filter; fruit fly algorithm; dynamic neighborhood adjustment

0 Introduction

Acoustic emission (AE) signals are non-stationary, non-linear transient elastic waves released during coal and gas outbursts. Monitoring AE behavior has gradually become an important means for preventing and controlling coal and gas outburst disasters in mines. However, due to the noisy environment at coal mining sites, sensor signals acquired by AE signal acquisition systems contain substantial noise interference, which severely impacts subsequent research on AE signal feature extraction, recognition, and prediction. Therefore, research on AE signal denoising is particularly critical.

To date, scholars have proposed various signal denoising methods that have achieved good results, though limitations remain. For instance, the classical Kalman filter is generally used for linear signal denoising and is unsuitable for non-linear, non-stationary AE signals. Wavelet analysis, employed for AE signal denoising in prior work, is constrained by the selection of wavelet basis functions, and its denoising performance is affected by this choice; moreover, it exhibits unsatisfactory precision for low signal-to-noise ratio signals. The empirical mode decomposition (EMD) denoising algorithm proposed in other research suffers from distortion when filtering high-frequency sequences and is prone to modal aliasing issues.

Particle filtering represents a relatively new filtering technique that is not constrained by system non-linearity or Gaussian noise distribution, making it applicable to any system describable by a state-space model and significantly broadening its scope of application. Building on this foundation, previous work proposed a particle filtering method under threshold denoising that achieved good results but failed to address the particle depletion problem in the resampling process, leaving room for further improvement in denoising precision.

Having analyzed these limitations, this paper proposes a method that employs a fruit fly optimization algorithm (FOA) with dynamic neighborhood (D) adjustment to optimize particle filtering (PF) for establishing an AE signal state-space model and processing AE signals from coal-gas outbursts. Compared with other denoising methods, this approach demonstrates superior denoising performance and compensates for the shortcomings of alternative methods.

2.1 Fruit Fly Algorithm

The fruit fly optimization algorithm is a swarm intelligence algorithm derived from biological foraging behavior that seeks global optimization. It leverages the advantages of fruit flies' vision and olfaction during foraging to design optimal solution search behavior, thereby performing iterative optimization and solving scheduling problems such as pipeline and resource-constrained projects.

This paper employs the fruit fly algorithm to optimize and improve the resampling process of particle filtering. Fruit fly populations represent signal point particles, and the algorithm' s excellent optimization capability yields more effective particles, solving the particle depletion problem.

Particle filtering is a Bayesian estimation method based on Monte Carlo principles that has been applied in signal processing, fault diagnosis, multi-target tracking, and other fields. The main idea of particle filtering for random signals is to approximate the random signal through weighted summation instead of integral operations in the state space. Through continuous updates of the system observation function, it achieves minimum variance estimation of random signals:

$$\hat{x}_{k|k} = \sum_{i=1}^{N} \omega_{ik} f(x_{ik}) = \sum_{i=1}^{N} \omega_{ik} x_{ik}$$

where ω_{ik} represents particle weights and N is the number of sampled particles.

In practice, the particle filtering denoising algorithm approximates the true state distribution of random signals to achieve noise filtering. Thus, the AE signal denoising problem studied in this paper is essentially transformed into a state estimation problem for the true distribution of AE signals.

To denoise AE signals using particle filtering, a random signal state-space model must first be established:

$$x_k = g(x_{k-1}, q_{k-1})$$

$$z_k = h(x_k, v_k)$$

where q_{k-1} is system noise at time $k-1$, v_k is observation noise, $g(\cdot)$ is the state transition function, and $h(\cdot)$ is the observation function.

The particle filter model is then initiated: at time $k = 0$, N signal points are sampled from the prior distribution $p(x_0)$ as initial samples with given initial weights $\omega_{i0} = 1/N$ for $i = 1, 2, \dots, N$. At time $k + 1$, signal points are sampled from the importance distribution $q(x_{k+1}|x_{ik}, z_{k+1})$ as preliminary estimates. If the number of effective signal points satisfies:

$$\hat{N}_{eff} = \frac{1}{\sum_{i=1}^{N} \omega_{ik}^2} < N_{thr}$$

the resampling process is entered, where signal points with larger weights are selected for replication and those with smaller weights are discarded.

The process based on fruit fly algorithm optimization of particle filter resampling is as follows:

a) **Initialization**: In equations (7) and (8), set $m = 0$ and initialize X_i^0, Y_i^0.
b) **Olfactory search**: Update paths according to equations (7) and (8) to find signal point particles with larger weights.
c) **Individual evaluation**: Calculate the smell concentration S_{ik} released by fruit fly individuals using equation (9).
d) **Visual search**: Select the fruit fly individual with $\max(S_{ik})$ as the found optimal solution.
e) **Termination criterion**: If the termination criterion is satisfied, output the particle with maximum weight; otherwise, set $m = m + 1$ and return to step b).

During the fruit fly algorithm optimization process, it is impossible to adjust the state of neighborhood particles according to each particle' s state and its neighborhood environmental parameters, making it prone to falling into local optima and unable to obtain precise global optimal solutions, which indirectly affects AE signal denoising precision.

Finally, set $k = k + 1$ and repeat the above process. When the maximum iteration count or precision requirement is met, output the estimated signal state:

$$\hat{x}_k = \sum_{i=1}^{N} \omega_{ik} x_{ik}$$

2.2 D-FOA Optimization Algorithm

To address the problem of being unable to seek global optimal solutions as described in Section 3.1, a regulatory factor—the diversity factor D—is introduced. D can reflect the degree of particle diversity, thereby achieving the purpose of controlling the number of neighborhood particles.

Let the set of maximum smell concentration values that fruit flies have reached be $\{M_{1k}, M_{2k}, \dots, M_{Nk}\}$. Take the maximum and minimum values of smell concentration, $M_{\max}$ and $M_{\min}$, and divide them equally into N small regions. The diversity factor can then be expressed as:

$$D = -\sum_{i=1}^{N} p_i \log(p_i)$$

where p_i represents the proportion of particles falling into each region, and $p_i = n_i/N$ (n_i is the number of particles in each region).

The specific control strategy for fruit fly individuals is: if the current D value of a fruit fly is smaller than the previous value, indicating reduced diversity of the fruit fly individual, the number of fruit flies in its neighborhood should be decreased; if the current D value is larger than the previous value, indicating increased diversity, the number of fruit flies in its neighborhood should be increased.

In this strategy, the number of neighborhood fruit flies is controlled by the following two equations:

Expansion factor:

$$U_i = \mathrm{Unumber}(i) + 1$$

Restriction factor:

$$V_i = \mathrm{dnumber}(i) - 1$$

where Unumber(i) represents the ranking index of the i-th fruit fly' s smell concentration value among all fruit flies (arranged in ascending order of function values), and dnumber(i) represents the ranking index of the i-th fruit fly' s objective function value among all fruit flies (arranged in ascending order of function values). neighbor(i) represents the set of neighborhood fruit flies for the i-th fruit fly, and Unumber(i) represents the number of neighborhood particles for the i-th particle.

The addition of the diversity factor D effectively controls the number of neighborhood fruit flies, improves the global optimization capability of fruit flies, accelerates convergence speed, enables particles to quickly move toward high-likelihood regions, and alleviates particle impoverishment.

3 AE Signal Denoising Based on D-FOA-PF Algorithm

3.1 AE Signal Denoising Algorithm Based on D-FOA-PF

Using the neighborhood dynamic adjustment fruit fly algorithm to optimize particle filtering, the state of AE signals is tracked. After multiple iteration cycles, particles reaching optimal objective values are used to predict the next

AE signal state, and the estimated AE signal state is output. The algorithm flowchart is shown in [Figure 1: see original paper].

The specific implementation steps are as follows:

a) **Initialization**: Assume a sequence of AE signals where the current signal has M signal points, and each signal point has N particles. At $k = 0$, sample from the prior distribution $p(x_0)$ and assign each particle weight:

$$\omega_{i0} = \frac{1}{N}, \quad i = 1, 2, \dots, N$$

b) **Importance sampling of signal points**:

$$x_{ik} \sim q(x_k | x_{i,k-1}, z_k)$$

c) **Importance weight calculation of signal points**: Determine weights from the current signal point state and measurement values:

$$\omega_{ik} = \omega_{i,k-1} \frac{p(z_k|x_{ik})p(x_{ik}|x_{i,k-1})}{q(x_{ik}|x_{i,k-1}, z_k)}$$

d) **Update particle iteration position and direction**: Update particle position and direction after m iterations through the fruit fly algorithm position formula:

$$X_{ik}^{m+1} = X_{ik}^{m} + \text{randomvalue} \times r$$

$$Y_{ik}^{m+1} = Y_{ik}^{m} + \text{randomvalue} \times r$$

e) **Calculation of particle objective function values for signal points**: First update the smell concentration judgment value using equations (15) and (16), then calculate the smell concentration value S_{ik} as the objective function value:

$$S_{ik} = \frac{1}{\sqrt{2\pi R}} \exp\left(-\frac{(z_k - z_{ik})^2}{2R}\right)$$

f) **Dynamic adjustment of neighborhood particle count for signal point particles**: Calculate the particle diversity factor D_{ik} using equation (10), and adjust the increase or decrease of neighborhood particle count according to the diversity control strategy.

g) **Determine D-FOA iteration stopping condition**: If particles reach maximum iteration count or obtain optimal values, terminate iteration. Otherwise, set $m = m + 1$ and return to step d) to reiterate for optimal solution.

h) **Normalization of signal point weights**:

$$\omega_{ik} = \frac{\omega_{ik}}{\sum_{j=1}^{N} \omega_{jk}}$$

i) **Signal point state estimation**:

$$\hat{x}_k = \sum_{i=1}^{N} \omega_{ik} x_{ik}$$

3.2 Denoising of Coal-Gas Outburst AE Signals Based on D-FOA-PF Algorithm

The time series of acoustic emission from coal-gas outbursts exhibits synchrony and overlap with seismic waves in distribution. Based on this characteristic, the AE signal time-domain model is characterized as:

$$X(t) = X_1(t) \sin[\omega(t) \cdot t + \delta(t)]$$

where $X(t)$ represents the random process of AE signals, $X_1(t)$ represents the random process of AE signal amplitude, ω is angular frequency, and δ is phase angle.

The discrete form is written using the Gauss-Markov process:

$$X_k = p_X X_{k-1} + q_{k-1}$$

where X_k is the AE signal time series, $p_X = e^{-\gamma \Delta T}$ is the constant between Gauss-Markov processes, q_{k-1} is system noise, ΔT is sampling interval, and $\gamma = \frac{1}{cT}$ is the Gauss-Markov process standard deviation.

Considering the noisy environment at coal mining sites, actual acquired acoustic emission signals contain substantial random noise. Therefore, random noise is taken as another state variable:

$$X_k = \begin{bmatrix} X_{1k} \\ X_{2k} \end{bmatrix}$$

where X_{1k} and X_{2k} are independent parameters.

The system state-space equation is established as:

$$\begin{bmatrix} X_{1k} \\ X_{2k} \end{bmatrix} = \begin{bmatrix} p_{X1} & 0 \\ 0 & p_{X2} \end{bmatrix} \begin{bmatrix} X_{1,k-1} \\ X_{2,k-1} \end{bmatrix} + \begin{bmatrix} q_{1,k-1} \\ q_{2,k-1} \end{bmatrix}$$

Based on the state equation, the observation equation is established as:

$$Z_k = C(X_k) + v_k = \sin[X_{1k} + \Delta\omega] + v_k$$

where $A(X_{k-1})$ represents the state transition model, B represents the coefficient matrix of system noise, Q_{k-1} represents the system noise matrix, $C(X_k)$ represents the non-linear observation function, and v_k represents observation noise.

On the basis of establishing the AE signal state-space model, the optimized particle filtering algorithm is executed for denoising acoustic emission signals as follows:

a) Input the acquired noisy AE signal and random noise signal into the state-space model to determine the parameters involved in the system equation.

b) Use the acquired noisy AE signal as the initial state of the model, and employ the neighborhood dynamic adjustment fruit fly algorithm to optimize the resampling process to obtain optimal sampling signal point particles.

c) Perform state estimation of the signal, calculate root-mean-square error and signal-to-noise ratio, and evaluate denoising performance.

4 Application of D-FOA-PF Algorithm to Coal-Gas Outburst AE Signal Denoising

A 50mm × 100mm formed coal sample was selected as the experimental specimen with a loading speed of 0.9 t/min and sampling frequency of 1 MHz. Various noises simulating mechanical operations, human activities, and natural sources at coal mining sites were added to the experimental environment. AE signal data during the coal rock mass loading deformation to fracture process was acquired through the AE signal acquisition system shown in [Figure 2: see original paper]. The original noise-contaminated emission signal is shown in [Figure 3: see original paper].

Initialize relevant parameters for the denoising algorithm: particle number $N = 500$, maximum fruit fly iteration count of 1000, particle weight $\omega_0 = 0.002$.

Using SNR and RMSE as evaluation metrics, these can be calculated using equations (24) and (25):

$$\mathrm{SNR} = 10 \log \frac{\sum_{i=1}^{N} s(i)^2}{\sum_{i=1}^{N} (s(i) - \tilde{x}(i))^2}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (s(i) - \tilde{x}(i))^2}$$

where $s(i)$ is the original signal and $\tilde{x}(i)$ is the denoised signal.

According to the spatiotemporal patterns of acoustic emission during coal rock mass fracture, it can be observed that the signal features in [Figure 3: see original paper] are submerged in substantial noise, making it impossible to identify effective components of AE signals. Standard PF, FOA-PF, and D-FOA-PF methods were respectively applied for denoising the acoustic emission signals. Through MATLAB simulation, the corresponding denoised signals are shown in Figure 4: see original paper-(c). In Figure 4: see original paper, the amplitude of the signal cluster portion is reduced, but the signal still exhibits many burrs during initial loading, indicating residual noise interference. Signals in Figure 4: see original paper and (c) show greater amplitude reduction compared to (a) and appear smoother, with signal (c) demonstrating more thorough noise reduction.

To deeply analyze the impact of noise signal distribution on AE signals and further validate the denoising effect of the improved PF method, fast Fourier transform (FFT) was performed on the three sets of time-domain signals in [Figure 4: see original paper], yielding three spectra shown in [Figure 5: see original paper].

When coal rock mass is in the fracture stage, AE signal spectra exhibit maximum signal intensity and highest main frequency band during fracture, with signal intensity weakening and main frequency decreasing as fracture develops. Figure 5: see original paper shows that noise is distributed across the entire frequency range, concentrated mainly in high-frequency regions. Comparing the spectra of the three denoising methods, the signal frequency distribution in Figure 5: see original paper is clearer, with the highest amplitude of the main frequency range reduced most significantly (reaching approximately 350). High-frequency 突变 signals are substantially reduced, demonstrating the best spectral characteristic pattern of coal rock mass fracture.

[Figure 6: see original paper] shows that during the initial iteration stage, the RMSE values of the three methods are similar. As iteration count increases, the distances between the three curves gradually widen, with curve 3 descending fastest and converging first. Curve 1 exhibits faster convergence than curve 2, a phenomenon caused by the fruit fly iteration falling into local optima.

At iteration conclusion, curve 3 achieves the smallest RMSE value. presents comparative values of signal-to-noise ratio and root-mean-square error. Comprehensive analysis of these data demonstrates the superior performance of the D-FOA-PF algorithm for AE signal denoising.

5 Conclusion

By integrating the fruit fly swarm intelligence optimization algorithm into the particle filtering method and dynamically adjusting the iteration process, this paper proposes a novel optimization algorithm to achieve better estimation of particle states, realizing the goal of filtering noise signals from acoustic emission signals during coal-gas outbursts.

a) The D-FOA improvement of the particle filter resampling process alleviates particle depletion, increases particle diversity, accelerates convergence speed, and enables signals to achieve high-precision denoising effects in relatively short time.

b) Qualitative analysis of acoustic emission signals through time-domain waveforms and spectrograms provides intuitive clarity of noise filtering effects. Quantitative analysis using SNR and RMSE evaluates filtering capability.

c) The acquired noisy AE signals were denoised using standard particle filtering, fruit fly optimized particle filtering, and improved particle filtering. Experimental results show that the improved particle filtering denoising method increases the signal-to-noise ratio by approximately 15.3 dB, reduces root-mean-square error to minimal values, largely preserves the time-domain waveforms and spectral characteristics of AE signals, improves the estimation accuracy of the denoising algorithm, and yields cleaner denoised signals compared with other optimization methods, laying a solid foundation for subsequent feature analysis and prediction.

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