Firefly Algorithm With Disturbance-Factor-Based Particle Filter for Seismic Random Noise Attenuation

Xue Han, Bin Wu, and Dong Wang

***Abstract*— Particle filter (PF) has been proven to be an effective method for seismic random noise attenuation. However, the sample impoverishment caused by resampling is an inherent problem, resulting in serious loss of valid seismic information and poor estimation accuracy. To solve the problem and to further improve the particle quality, we propose the firefly algorithm with disturbance-factor-based PF (FA-PF). In this method, we introduce the strategy of FA to simulate the movement process of particles instead of the resampling and optimize the FA method. We optimize the FA from three aspects. First, we adopt the global optimal value to guide the particle brightness update, improving the ability of global optimization and decreasing the probability of the local optimum. Then, the attraction decreases as the number of iterations increases, reducing particle oscillation. Finally, we apply a disturbance factor in the location update period, increasing the proportion of meaningful particles and further optimizing the distribution of particles. The experimental results show that particle diversity is well-maintained and the particles can represent the valid signal more accurately, which indicates that the FA-PF method performs better in suppressing the random noise and preserving the valid signal than the PF.**

***Index Terms*— Disturbance factor, firefly algorithm (FA), particle filter (PF), random noise, seismic denoising.**

I. Introduction

SIGNAL processing is a technique of electronics field which is useful to apply in modern seismic data processing. Seismic data are always corrupted by random noise, influencing the acquisition of geological information. Therefore, the noise elimination is an essential step in seismic data processing.

Many approaches have been developed to suppress seismic random noise, such as wavelet transform, wiener filter, time–frequency peak filter (TFPF), radon transform (RT), empirical mode decomposition (EMD), f-x deconvolution, and polynomial approximation. TFPF can give an unbiased estimation of the signal in cases where it is linear in time and contaminated by stationary white Gaussian noise [1], [2]. Shearlet transform is derived from wavelet transform, and it offers a directional multiscale framework with the ability to precisely analyze functions and distributions, but the high-frequency bands are also filtered out with the noise [3], [4]. RT transforms the irregular spatial sampling data to the radon panel and then transforms the data back to the regular spatial grid to reconstruct the regular seismic data [5].

Particle filter (PF) has been successfully applied in seismic random noise attenuation by Han *et al.* [6]. The seismic state-space model can be described as a nonlinear system; PF is an effective nonlinear estimating method and produces an optimal value by uniting observation information and prior knowledge [7]. In addition, PF is based on the signal generation model, and thus it can obtain the time-varying characteristics of the seismic signal. However, particle impoverishment is an inherent problem in PF, resulting in the loss of seismic information. Hence, the particles perform poorly in signal preservation and, therefore, hinder the seismic data processing in the case of low signal-to-noise ratio (SNR).

Recently, various novel methods based on swarm intelligence optimization have come forward to prevent particle impoverishment. The firefly algorithm (FA) is an advanced intelligence optimization algorithm [8]. In this letter, we propose the firefly algorithm with disturbance-factor-based particle filter (FA-PF) method to improve the performance of PF in seismic denoising. The FA-PF method adopts the strategy of the FA to improve the particle quality and address the impoverishment problem. To avoid the probability of the local optimum [9] and the oscillatory behavior [10] in the FA, we optimize the FA method. Particularly, a disturbance factor is applied in the location update process to further optimize the distribution of particles. Consequently, particle diversity can be retained and the particles can accurately represent the reflected signal, improving the estimation accuracy. The rest of this letter is organized as follows. Section II introduces the basic principles of PF and the particle impoverishment issue. Meanwhile, we establish a state-space model for seismic records. In Section III, we present the framework of the proposed FA-PF. Section IV shows the performance of our proposed method on both the synthetic models and field data. Finally, the conclusions are presented in Section V.

II. Particle Filter For Seismic Random Noise Attenuation

A. State-Space Model for Seismic Data

Seismic denoising is an estimation problem that evaluates the reflected signal from the noisy seismic data. To ensure

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X. Han and D. Wang are with the Changchun Institute of Optics, Fine Mechanics and Physics, Chinese Academy of Sciences, Changchun 130033, China (e-mail: hanxue030609@sina.com).

B. Wu is with the School of Energy and Power Engineering, Xi'an Jiaotong University, Xi'an 710049, China (e-mail: wubin030609@sina.com).

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that the proposed method is applied efficiently and reliably, a state-space model of the seismic data is needed for seismic denoising. The generation model of seismic signals is nonlinear, and thus, a time-varying autoregressive (TVAR) model is used to construct the state transition model as follows:

$$x_k = \sum_{i=1}^{p_k} b_{i,k} x_{k-i} + u_k \tag{1}$$

where x_k represents the reflected signal at time k; $b_{i,k}$ and p_k denote the parameter and the order of the TVAR model, respectively; u_k is an independent random variable with a Gaussian distribution that represents the system error in the establishment of the state transition model. The state transition model (1) describes the evolution process of the reflected signal.

When the noisy seismic data y_k received at the ground surface are corrupted by the additive random noise, the measurement equation can be modeled as

$$y_k = H_k x_k + \upsilon_k \tag{2}$$

where y_k is the noisy seismic signal, υ_k is the independent measurement noise, and it represents the noise of seismic data. H_k is the linear observation matrix.

B. Principles of Particle Filter

In PF, the main idea is to use a set of random weighted particles to estimate the unobservable state variable x_k through the observation variables $y_{1:k} = \{y_1, \ldots, y_k\}$. Consequently, the state variable x_k can be approximated as

$$x_k = \sum_{i=1}^{N_p} \omega_k^i x_k^i \tag{3}$$

where x_k^i and ω_k^i are the ith particle and the associated weight, respectively, and N_P is the number of particles. The PF consists of three main steps: sampling, weight updating, and resampling [11].

1) Sampling: particles are sampled according to the proposal density function $q(x_k^i|x_{k-p_k:k-1}^i, y_k)$. In this letter, we choose the most popular choice, that is, $q(x_k^i|x_{k-p_k:k-1}^i, y_k) = p(x_k^i|x_{k-p_k:k-1}^i)$.
2) Weight updating: a new measurement is available, and the weights are calculated as

$$\omega_k^i = \omega_{k-1}^i p\left(y_k|x_k^i\right) \tag{4}$$

3) Resampling: particles with low weights are eliminated and particles with high weights are replicated.

III. Firefly Algorithm With Disturbance-Based Particle Filter for Seismic Random Noise Attenuation

In PF, the resampling introduces a negative issue, that is, sample impoverishment, leading to the diversity of particles being decreased and the information capacity of the final particle set being seriously reduced. Hence, the particles are difficult to accurately represent the reflected signal. To solve this problem, we propose a FA-PF to seismic denoising.

A. Firefly Algorithm

The FA was developed by Yang [12], and the algorithm is guided by three basic principles as follows.

1) All fireflies are unisex and any firefly can attract others.
2) The degree of the firefly attraction is proportional to brightness and decreases with distance. For any two fireflies, the brighter one attracts the other.
3) The brightness of a firefly is determined by its performance in the objective function.
4) The brightness I_{ij} and attraction β_{ij} are defined as

$$I_{ij} = I_0 e^{-\gamma r_{ij}^2} \tag{5}$$

$$\beta_{ij} = \beta_0 e^{-\gamma r_{ij}^2} \tag{6}$$

where I_0 and β_0 denote the initial brightness intensity and the initial attraction, respectively; γ represents the light absorption coefficient and can take any value within [0.01,100]; r_{ij} is the distance between any two fireflies i and j.

A low brightness firefly x_i will be attracted by a high brightness firefly x_j as

$$x_i = x_i + \beta_{ij}(x_j - x_i) + \alpha(\text{rand} - 0.5) \tag{7}$$

where x_i and x_j represent the location of the ith firefly and the jth firefly, respectively; $\alpha \in [0, 1]$ is the step size and rand is a random number generator uniformly distributed in the range from 0 to 1.

B. Firefly Algorithm With Disturbance-Factor-Based Particle Filter for Seismic Random Noise Attenuation

The PF shows that the optimal value is evaluated by updating the weights and location of particles, while the FA updates the brightness and the location of the fireflies to approximate the optimal filters [13]. On account of their similarities, we apply the FA algorithm in PF and propose the FA-PF method to seismic denoising. In this method, after the process of weight updating (i.e., particles expressed as $\{x_k^i, \omega_k^i\}_{i=1}^{N_p}$), the particles undergo a location update process based on the FA instead of resampling.

First, the brightness of the particle is defined as

$$I_i = I_0 e^{-\gamma r_i^2} \tag{8}$$

where I_i is the brightness of the particle x_k^i at time k, and r_i is the distance between particle x_k^i and particle x_k^{best} defined as

$$r_i = \left\|x_k^i - x_k^{\text{best}}\right\| \tag{9}$$

where x_k^{best} is the global optimal particle at time k. In PF, the only information that can measure the quality of the particles is the weight, so we choose the particle with the highest weight as the optimal particle. The particle set has only one global optimum at time k, and consequently, each particle only interacts with x_k^{best}, reducing the computational complexity from $O(N^2)$ to $O(N)$. Besides, the global optimum directs the movement process of the particle, improving the ability of global optimization and decreasing the probability of the local optimum.

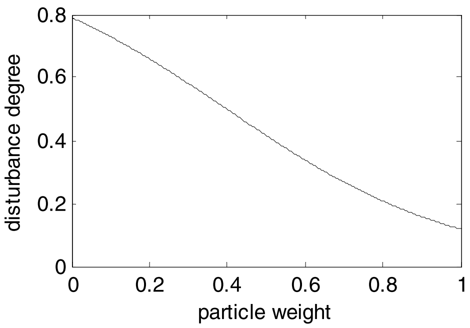


Fig. 1. Relationship between the particle weight and the disturbance degree.

TABLE I
FA-PF

Iterations:
For k = 1, 2, . . . do
1. Sample: particles are sampled according to the proposal density function $q(x_k^i \mid x_{k-1}^i, y_k)$
2. Weight update: weights are updated as (4).
3. Location update:
Choose the particle with maximum weight as the global optimal particle x_k^{best}.
Calculate the brightness as (8).
Update the location of the particle as (11).
Calculate the corresponding weight of the updated particle as (4).
4. State estimation: estimate the state $x_k = \sum_{i=1}^{N_p} w_k^i x_k^i$

In the FA, the attraction determines the movement length and as the distance increases. In the early iterations, the attraction is weak due to the long distance between the particles, and the movement length is short; as a result, the particles tend to fall into the local optimum. Conversely, in the later iterations, the attraction is strong and the movement length is long, and hence, the particles oscillate near the extreme point on account of the long distance of the movement. Thus, we redefine the attraction of the particle as

$$\beta_i = \beta_0 e^{-\gamma r_i^2} \left(\frac{1}{1+k^2} + 0.5 \right). \tag{10}$$

Obviously, the attraction decreases as the number of iterations increases, and finally remains near the minimum. Therefore, this method can effectively overcome particle oscillation. Now, the particle x_k^i is attracted to the global optimal particle x_k^{best} with the influence of the disturbance factor K_i as

$$x_k^i = x_k^i + \beta_i \left(x_k^{\text{best}} - x_k^i \right) + K_i(\text{rand} - 0.5). \tag{11}$$

To further optimize the distribution of particles, we set the disturbance factor K_i in the particle movement as

$$K_i = 1 \Big/ \left(1 + \exp\left(\frac{w_k^i - w_k^{\text{avg}}}{w_k^{\text{best}} - w_k^{\text{avg}}} \right) \right) \tag{12}$$

where w_k^{avg} and w_k^{best} denote the average and the optimal weights at time k, respectively. The particle weight is the only standard to measure the quality of the particle; hence, the disturbance factor K_i takes full advantage of the weight to control the degree of disturbance as (12). Fig. 1 depicts the relationship between the particle weight and the degree of disturbance. A low-weighted particle undergoes a strong disturbance progress and is guided by the global optimal particle. As a result, the convergence rate is accelerated and the ability of global searching is improved. Conversely, a particle with high weight protects its excellent properties from damage by a weak disturbance process; meanwhile, the particle diversity is well-maintained. In this way, the final particle set is not only diverse but also of high quality. Therefore, the vital seismic information is obtained and the particles provide a better representation of the desired signal.

The FA-PF is summarized in Table I.

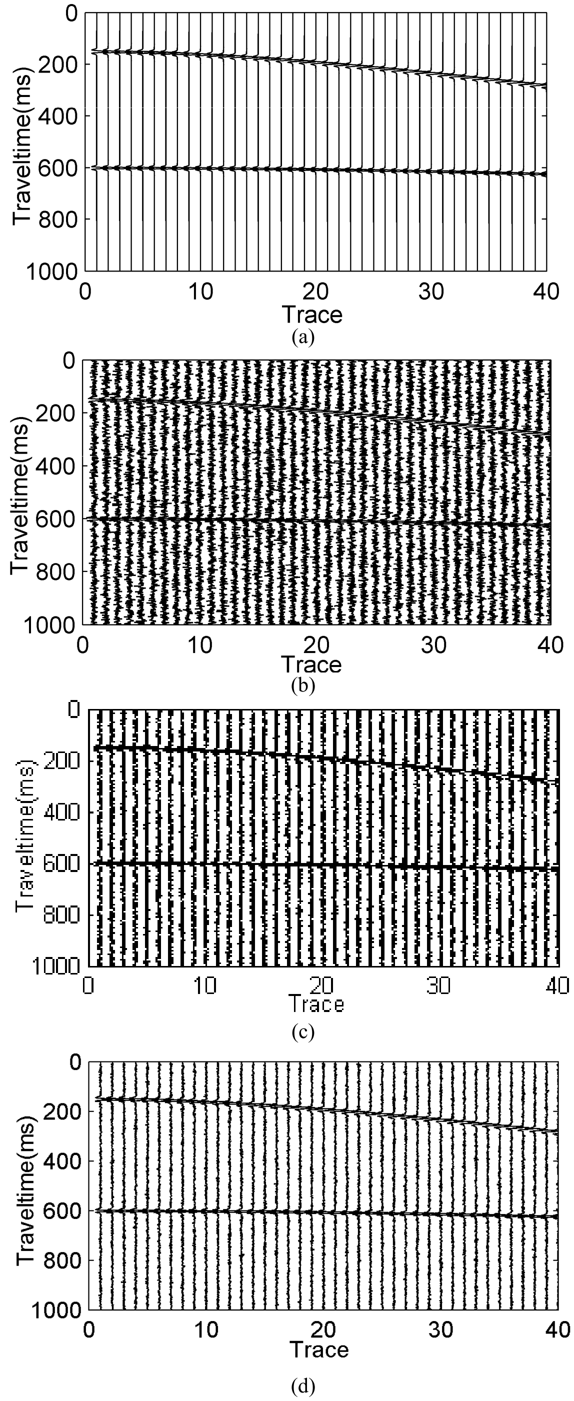


Fig. 2. Results of a synthetic seismic record. (a) Pure record. (b) Noisy record. (c) Result of PF. (d) Result of FA-PF.

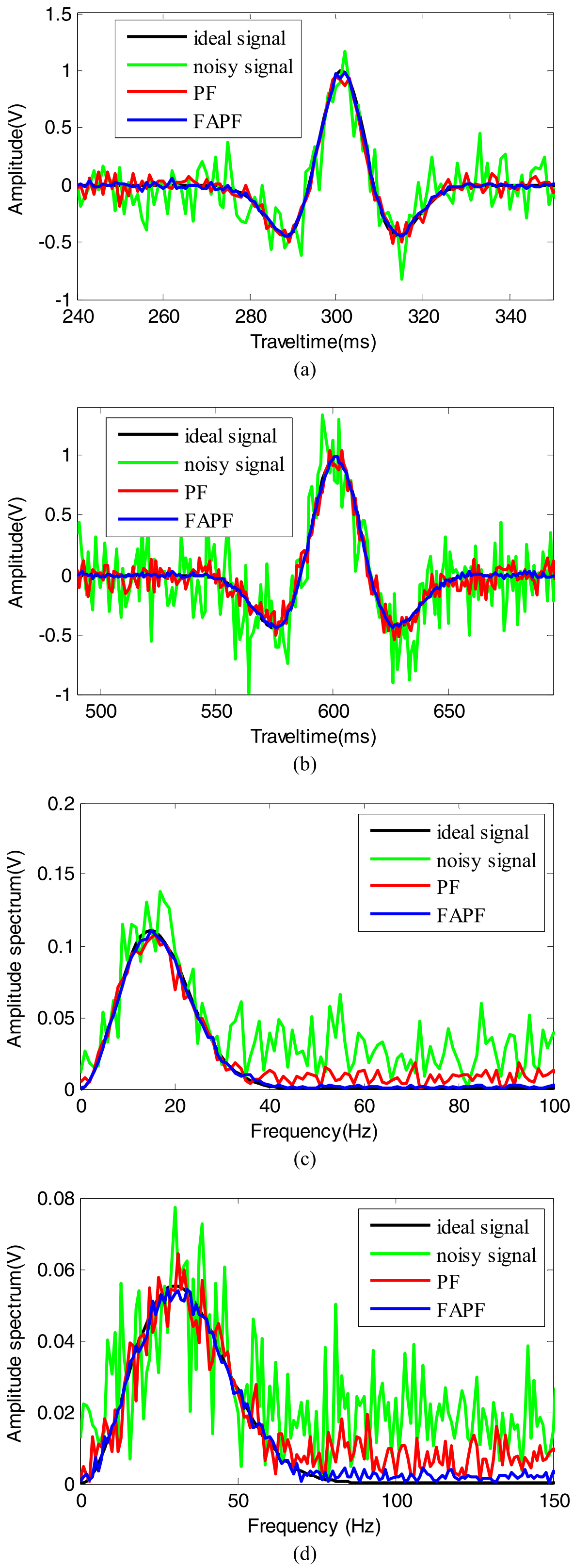


Fig. 3. (a) Waveform comparison of the shallow layer signal. (b) Waveform comparison of the deep layer signal. (c) Spectrum comparison of the shallow layer signal. (d) Spectrum comparison of the deep layer signal.

IV. Application to Seismic Records

A. Synthetic Seismic Record

We first test the performance of the proposed method on a synthetic seismic record. The dominant frequencies of two reflection events are 30 and 35 Hz, respectively. The noisy record is obtained by adding white Gaussian noise with the SNR of −5 dB, and the reflection events are almost submerged in the strong noise. Fig. 2(a) and (b) shows the pure record and the noisy record, respectively. Fig. 2(c) and (d) shows the filtered results after PF and the proposed FA-PF, respectively. We can see that the PF method can suppress some of the random noise, but the denoising result is not satisfactory. We extract the 40th trace from the denoised records for a further comparison. From Fig. 3(a) and (b), it can be observed that the amplitudes of the two wavelets filtered by FA-PF are much more close to the original signal, and both the low-frequency and high-frequency noises are suppressed to a significantly lower level as shown in Fig. 3(c) and (d).

TABLE II
SNR and MSE of the Filtering Results

Original record(dB)	PF		FA-PF	
	SNR(dB)	MSE	SNR(dB)	MSE
5	10.1658	0.0031	12.8671	0.0016
0	6.2542	0.0080	8.9542	0.0053
-5	4.8683	0.0152	7.6507	0.0103
-10	0.1532	0.0266	2.3379	0.0141

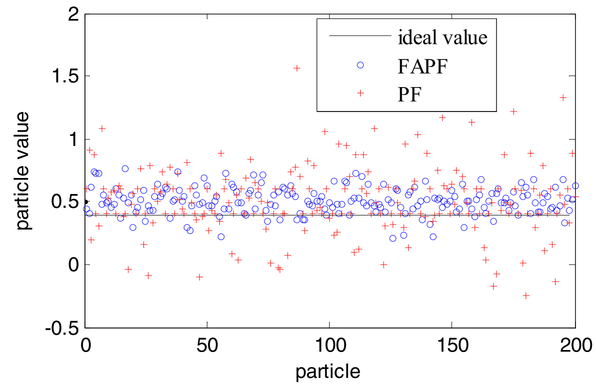


Fig. 4. Distribution of particles from the 592th sampling point in the 40th channel.

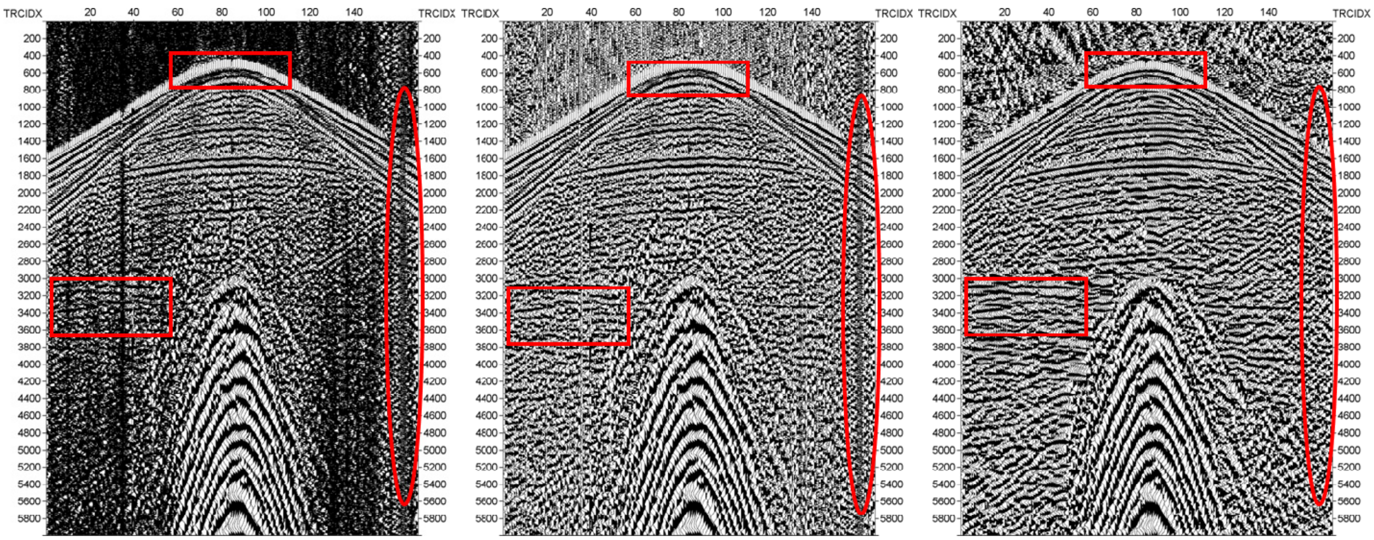
To evaluate the particle quality, we choose the 592th sampling point from the 40th channel and make a comparison on the particle distribution of the two methods in Fig. 4. The particle set in PF deviates seriously from the ideal signal, while the particles in FA-PF are more concentrated around the ideal signal, which means that the number of meaningful particles of FA-PF remains at a higher level than PF. Moreover, the proportion of the same-value particles is decreased in FA-PF, indicating that the particle diversity is protected.

To further compare the denoising and signal preservation ability of the proposed method, we use the following formula to compute the SNR and mean square error (MSE):

$$\mathrm{SNR(dB)} = 10\log_{10}\frac{\sum_{k=1}^{P}|s_k|^2}{\sum_{k=1}^{P}|s_k - x_k|^2} \tag{13}$$

$$\mathrm{MSE} = \frac{1}{P}\sum_{k=1}^{P}(s_k - x_k)^2 \tag{14}$$

where x_k is the filtered signal, s_k is the original signal, and P is the length of the signal.



(a) (b) (c)

Fig. 5. Result comparison. (a) Original field seismic data. (b) Result of PF. (c) Result of FA-PF.

Table II shows the SNR and MSE after denoising by two methods. As we can see from the figures, it is obvious that the performance of the proposed algorithm is better in random noise attenuation and valid signal preservation.

B. Field Data Processing

We apply two filtering methods to field seismic data obtained in a certain region of China, as shown in Fig. 5(a). The receiver interval is 30 m and the traces are sampled with a frequency of 1000 Hz. The distance between the source and the receivers changes from 600 to 3600 m. From the figure, we observe that the strong random noise seriously obscures the whole record and damages the continuities of the reflected events. To prove the feasibility and usefulness of our method in seismic denoising, we contrast the filtering results of PF and FA-PF. Note that the FA-PF result shown in Fig. 5(d) is better than the PF result in Fig. 5(c). The reflection events are sharper and more continuous by our method. To highlight this, we marked certain parts with ellipses and rectangles. As seen from these parts, the FA-PF method works well on real seismic records.

V. Conclusion

The FA-PF method has been proposed in this letter as an improvement to the PF. The novel method uses the strategy of FA to simulate the location update process of particles instead of the resampling, addressing the impoverishment problem. In the new method, we revise the mechanism of brightness and attraction, improving the ability of global optimization and reducing the computational complexity. To further optimize the distribution of particles, a disturbance factor is applied in the location update process. Therefore, the final particle set obtains the effective seismic information and reproduces the true signal more reliably. Tests on synthetic seismic data and field seismic data demonstrate that our method can suppress random noise significantly and improve reflection events continuously and clearly.

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