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Inversion method of pre-stack AVO parameter based on adaptive differential evolution algorithm[1]

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Abstract. Pre-stack parameter inversion technology based on the combination of intelligent algorithm and AVO (Amplitude Variation with Offset) provides an effective identification method for oil and gas exploration, but the traditional intelligent iterative algorithm such as genetic algorithm, when solving the problem, there exist some problems, such as the higher dependence of the algorithm on the initial model, the fast convergence, falling into the local optimum easily and so on, thus leading to the undesirable inversion effect. In order to solve the above problems, the adaptive differential evolution algorithm was combined with AVO parameter inversion in this paper to study the pre-stack inversion method based on adaptive differential evolution algorithm, which is more suitable for solving the problems of pre-stack AVO parameter inversion. This method has low dependence on the initial model, strong global convergent ability, simple operation and fast computation speed, which is very suitable for solving the problems of pre-stack AVO parameter inversion based on real number code.

Key words. Adaptive differential evolution algorithm, AVO technology, parameter inversion.

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1. Introduction

Seismic exploration is a method to carry out the oil exploration by using seismic information, because seismic information can reflect the changing trend of reservoir parameters, this method can be used to predict reservoir parameters. Seismic data is divided into pre-stack and post-stack, because the pre-stack seismic data include

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more information of the fluid than post-stack seismic data, and pre-stack inversion method has obvious advantages of stable results, high resolution, strong controllability and others, in recent years, the inversion based on pre stack seismic data has always been a hot topic in the field of seismic exploration. AVO (Amplitude Variation with Offset) [1], [2] technology is the most commonly used technology to predict oil and gas by using the pre-stack data, which can make full use of seismic data, and has been widely used in oil and gas detection. Pre-stack seismic data contain much useful information, which can be used to predict the condition of the underground oil and gas, among which, the three elastic parameters including P-wave velocity V_{p}, S-wave velocity V_{s} and density ρ are the key parameters. The three elastic parameters can reflect the saturation condition of underground oil and gas, and the relationship between P-wave velocity V_{p} and gas saturation is nonlinear, while the relationship between density ρ and gas saturation is linear, and S-wave velocity V_{s} can reflect some characteristics of rock. Therefore, it is necessary to collect the information of changes of these three elastic parameters when judging the saturation of underground oil and gas. It is usually necessary to construct a suitable nonlinear objective function for the inversion of pre-stack AVO elastic parameters, and then the objective function is optimized. When using a linear or quasi linear method to solve the problem, because these methods have strong dependence on the initial model and other defects, if the initial model is wrong, it will cause that the inversion result is not reliable; especially when solving the problem of nonlinear inversion with characteristics of multi parameters, multi peak, etc., these linear inversion methods would encounter a bottleneck.

In mid-1980s, nonlinear global intelligent optimization inversion technique had began to receive the attention of experts and scholars in geophysical field, and many new ideas and new methods in other fields had been continuously introduced to the geophysical field. In the past thirty years, this series of nonlinear global intelligent optimization inversion techniques have been widely used in various types of inversion problems, and have made many significant research results [3]–[6].

The experts and scholars have tried to combine the intelligent algorithm with other algorithms to realize the hybrid optimization inversion so as to improve the inversion precision [7]–[12]. For the inversion problem of traditional three-parameter, the S-wave velocity and the P-wave velocity often be a good inversion, but the density ρ is very poor, which is also an urgent problem to be solved.

2. AVO parameter inversion problem

2.1. Parameter inversion model

The establishment of inversion model mainly includes three steps. The first is to calculate the reflection coefficient R_{pp}. The Aki & Rechard approximate equation [13] was used in this paper. R_{pp} is calculated as formula

$$R_{\mathrm{pp}}(\theta) = \frac{1}{2}(1+\tan^2\theta)\frac{\Delta V_{\mathrm{p}}}{\overline{V_{\mathrm{p}}}} - (4\gamma^2\sin^2\theta)\frac{\Delta V_{\mathrm{s}}}{\overline{V_{\mathrm{s}}}} + \frac{1}{2}(1-4\gamma^2\sin^2\theta)\frac{\Delta\rho}{\bar{\rho}}\,, \qquad (1)$$

where, ΔV_{p}, ΔV_{s} and $\Delta\rho$ respectively represent the difference between V_{p}, V_{s} in the upper and lower two layers and ρ, $\overline{V_{\mathrm{p}}}$, $\overline{V_{\mathrm{s}}}$ and $\overline{\rho}$ respectively represent the means of V_{p}, V_{s} in the upper and lower layers and ρ , and θ refers to the angle calculated by real data, $\gamma = \frac{V_{\mathrm{s}}}{V_{\mathrm{p}}}$, while R_{pp} can be calculated according to this formula and is used as a component of the convolution operation of seismic records.

The second is to get seismic wavelet. Seismic wavelet is another component of convolution model of seismic records, and the data of seismic records are obtained according to the convolution calculation of wavelet and reflection coefficient, which is suitable for the establishment of forward model and making synthetic seismogram, while Ricker wavelet was used in this paper, which is a kind of zero-phase seismic wavelet, and its expression is as equation

$$f(t) = (1 - 2\pi^2 V_{\mathrm{m}}^2 t^2) e^{-\pi^2 V_{\mathrm{m}}^2 t^2}\,, \tag{2}$$

where V_{m} represents frequency, and t represents time, which could be set manually.

The third is to carry out the convolution operation with reflection coefficient and Ricker wavelet, as in equation

$$s(\theta) = R_{\mathrm{pp}}(\theta) * f(t) + n(t)\,, \tag{3}$$

where $R_{\mathrm{pp}}(\theta)$ represents reflection coefficient function, $f(t)$ represents seismic wavelet, and $n(t)$ represents the noise. Noise factors were not considered in this paper. The calculated $s(\theta)$ is used to construct the objective function.

2.2. *Objective function*

The simulation-optimization method is to convert the pre-stack AVO parameter inversion problem into an optimization problem and then the problem is solves by using optimization algorithm. From the optimization point of view, when the difference between the inversion seismic data generated from the optimized elastic parameters and the actual seismic data is 0 or less than a threshold, this elastic parameter is considered to be in accordance with the requirements. Because the individual would be evaluated by optimization algorithm according to the fitness function converted from the objective function, the quality of the constructed objective function for the inversion problem is the main factor to affect the inversion effect of pre-stack AVO elastic parameters. In this paper, firstly, the Aki & Rechard approximate equation was used to calculate the value of R_{pp}, that is the reflection coefficient of reflected P-wave, and then R_{pp} and wavelet were carried out with convolution to obtain the synthetic seismogram data. Sampling points were set as n and each sampling point required m different angles to calculate $n \times m$ seismic record data. Finally, the difference of m sets of seismic record data obtained by optimization of each sampling point subtracting the actual seismic record data was squared, which was divided by m after the cumulative sum, and then the data obtained from the n sampling points were divided by n after the accumulation, while after the final results were squared, that is what is required. According to the above formula, the inversion objective function can be established as in equation

$$f(x) = \sqrt{\frac{\sum_{i=1}^{n}\sum_{j=1}^{m}(s(\theta_{i,j}) - s'(\theta_{i,j}))^2}{n \times m}}\,, \tag{4}$$

where $s(\theta_{i,j})$ refers to forward seismic record and $s'(\theta_{i,j})$ refers to inverted seismic record.

3. Pre-stack AVO parameter inversion method based on adaptive differential evolution

Differential evolution (DE) [14], [15] was first proposed by Storn and Price in 1995. DE is a kind of adaptive global optimization algorithm based on population, which belongs to the evolutionary algorithm and has the advantages of simple structure, easy implementation, fast convergence and strong robustness. Due to the fact that the real coding is usually used in pre-stack AVO elastic parameter inversion problem, in this paper DE which is suitable for real coding was used to solve the problem. jDE algorithm [16] is a kind of parameter adaptive differential evolution algorithm. In the jDE algorithm, the population size N is set to a fixed value, and remains unchanged during the evolution, the control parameters CR and F are encoded directly into the individual and updated with certain rules.

The individual in the algorithm consists of inversion parameters. For the actual log model, each sampling point is a layer, i.e. one dimension. Since the three-parameter inversion is studied in this paper, the individual length is three times of the sampling point. Assuming that there are n sampling points, the parameters of the model are $3 * n$, and the corresponding coding method is

$$G_i = (V_{\mathrm{p}1}, V_{\mathrm{s}1}, \rho_1, \cdots, V_{\mathrm{p}j}, V_{\mathrm{s}j}, \rho_j, \cdots, V_{\mathrm{p}n}, V_{\mathrm{s}n}, \rho_n)\,. \tag{5}$$

In this paper, we use the traditional real number coding to design the individual (chromosome) in population space. The population is initialized by random initialization in a certain range. Each chromosome consists of a set of real numbers. Assuming that the population size is N, where $V_{\mathrm{p}j}, V_{\mathrm{s}j}, \rho_j$ represent the values of the three parameters corresponding to the j sampling points of individual G_i whose change range is set according to the actual logging data. The structure of the population space is shown in Fig. 1.

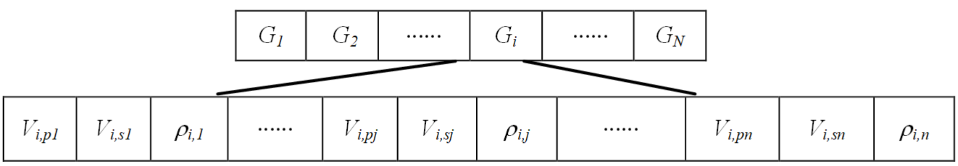

Fig. 1. Population space

The number of individual in the population is set n. Each individual is represented by a one-dimensional array with the length of $3 * n$. The initial value of the individual is selected within a limited range of experience (bound function constraint). Then the genetic algorithm is used to optimize each parameter. Finally, an optimal individual is obtained, that is, the optimal set of elastic parameters. Bound range constraints are as equation

$$\begin{array}{l} 0.8 \cdot V_{\mathrm{pwell}} \leq V_{\mathrm{p}} \leq 1.2 \cdot V_{\mathrm{pwell}}, \\ 0.8 \cdot V_{\mathrm{swell}} \leq V_{\mathrm{s}} \leq 1.2 \cdot V_{\mathrm{swell}}, \\ 0.9 \cdot \rho_{\mathrm{well}} \leq \rho \leq 1.1 \cdot \rho_{\mathrm{well}}. \end{array} . \tag{6}$$

The jDE algorithm uses the difference strategy to realize the individual variation. The differential strategy used in this paper is to select two different individuals in the population randomly whose vector difference is scaled with the vector to be changed. Specific methods are as equation

$$\begin{array}{l} V_i\left(g+1\right) = X_{\mathrm{r1}}\left(g\right) + F_i\left(X_{\mathrm{r2}}\left(g\right) - X_{\mathrm{r3}}\left(g\right)\right), \quad r1 \neq r2 \neq r3 \neq i, \\ F_i = \left\{ \begin{array}{cc} rndreal_i\left[0.1, 1\right], & rndreal\left[0,1\right] < \tau_1, \\ F_i, & \text{otherwise}, \end{array} \right. \end{array} , \tag{7}$$

where $r1$, $r2$ and $r3$ are three different random numbers which are different from the current individual numbering i with the range of [1, N]. F_i is a scaling factor for current individual, g represents the $g-th$ generation. $\tau_1 = 0.1$ means the probability of regulating F_i.

The purpose of the crossover operation is to randomly select individuals, because differential evolution is also a random algorithm. Cross operation method is shown in equation

$$\begin{array}{l} U_{i,j}\left(g+1\right) = \left\{ \begin{array}{cc} V_{i,j}\left(g+1\right), & rndreal\left[0,1\right] \leq CR_i \ or \ j = rndreal[0,3n], \\ X_{i,j}\left(g\right), & \text{otherwise}, \end{array} \right. \\ CR_i = \left\{ \begin{array}{cc} rndreal_i\left[0.1, 1\right], & rndreal\left[0,1\right] < \tau_2, \\ CR_i, & \text{otherwise} \end{array} \right. \end{array} , \tag{8}$$

where CR_i is the crossover probability of current individuals, $\tau_2 = 0.1$ means the probability of regulating CR_i.

4. Experimental simulation and analysis

The data of log data in the first data set were data of 241 sampling points, including P-wave velocity V_{p}, S-wave velocity V_{s} and density. Each sampling point corresponded to 8 different angles: [0°, 6°, 1°, 17°, 23°, 29°, 34°, 40°], which were used in each data set. The forward modeling of well logging curve model was made by using Aki & Rechard equation. The reflection coefficient was calculated by the log curve model. And then the reflection coefficient and wavelet were convoluted. Because the seismic records need to use the relationship between the upper and lower two groups of sampling points, the seismic data contains $240 * 8$ data. The resulting log data are shown in Fig. 2.

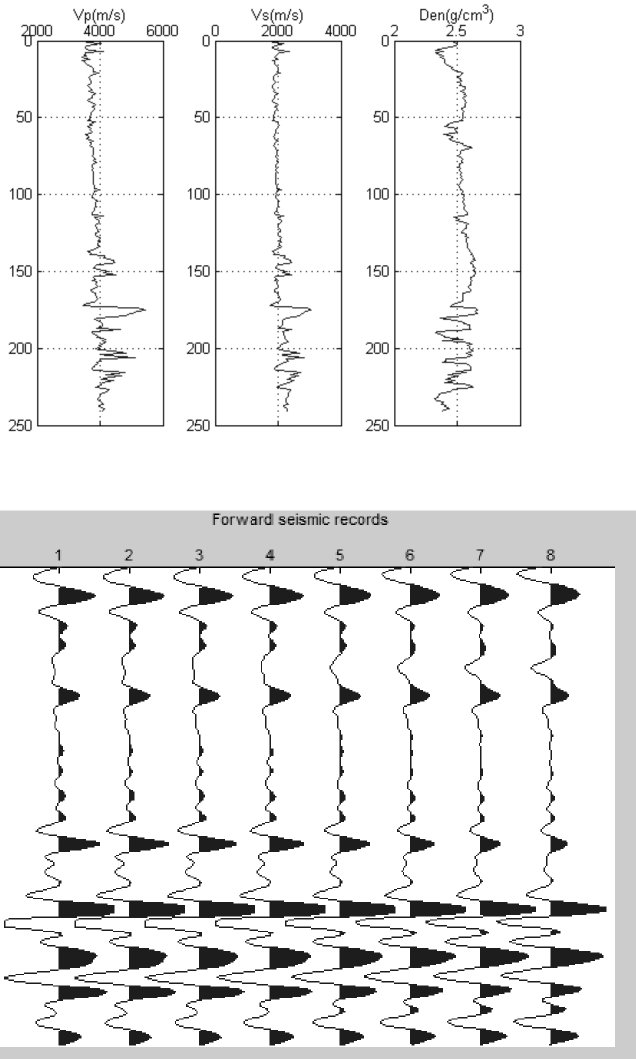

Fig. 2. Original logging curves and seismic records of theory model

Basic genetic algorithm (Basic GA), hybrid intelligent algorithm (STNGA) [17] and the proposed adaptive differential evolution (jDE) were used to carry out inversion of pre-stack AVO elastic parameters. The experiment was performed according to the previous algorithm parameter settings, and the experimental results can be obtained as shown in Fig. 3–Fig. 5.

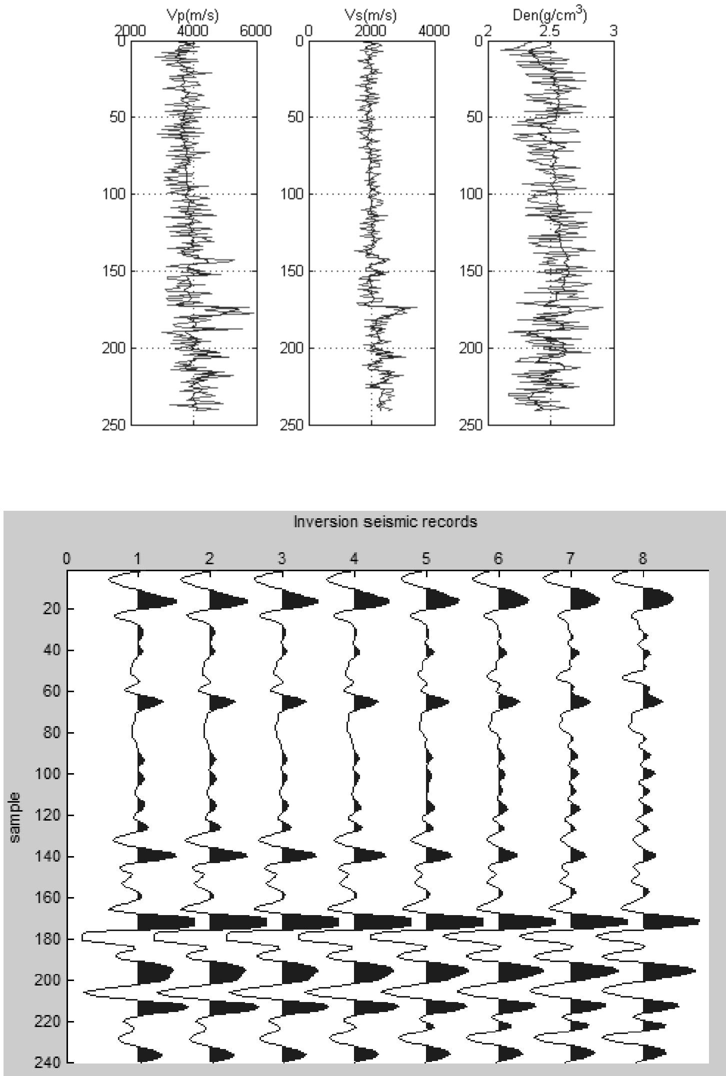

Fig. 3. Logging curves and seismic records of inversion generated by Basic GA

It is observed from Fig. 3–Fig. 5, jDE is better than simple genetic algorithm and improved intelligent hybrid algorithm, since it is close to the actual logging data and

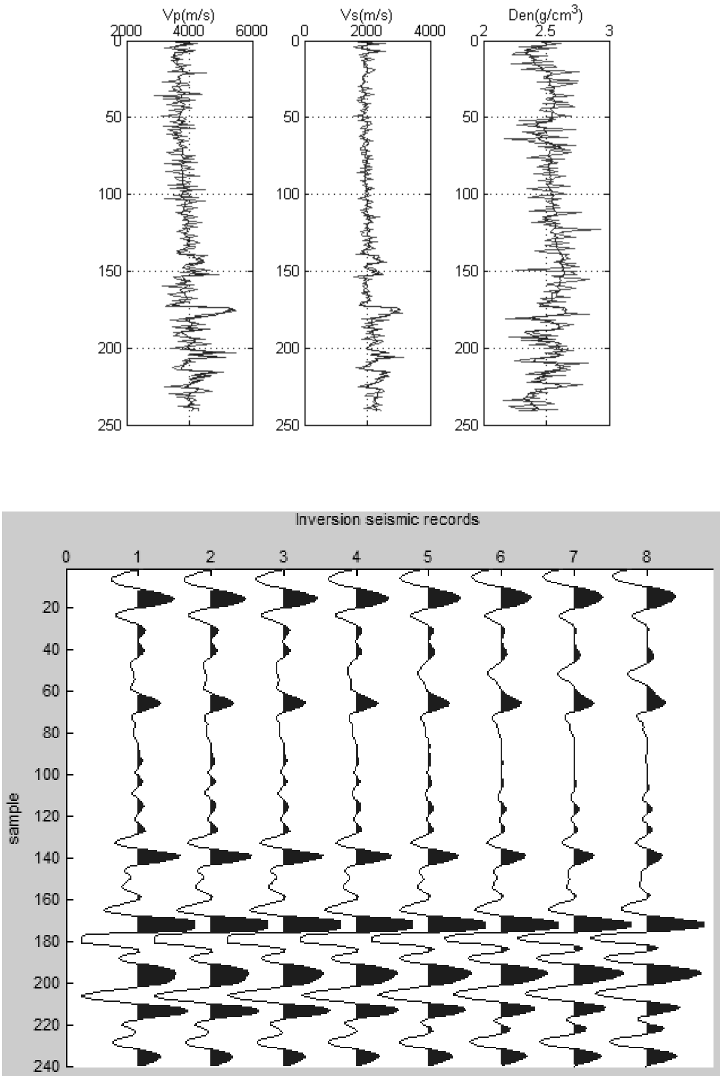

Fig. 4. Logging curves and seismic records of inversion generated by STNGA

the inverted seismic data are also in good agreement with the actual seismic data.

The experimental results of the simple genetic algorithm and the hybrid intelligent algorithm and the adaptive differential evolution algorithm were compared with each other by inversion. In the early stage of the algorithm, the convergence

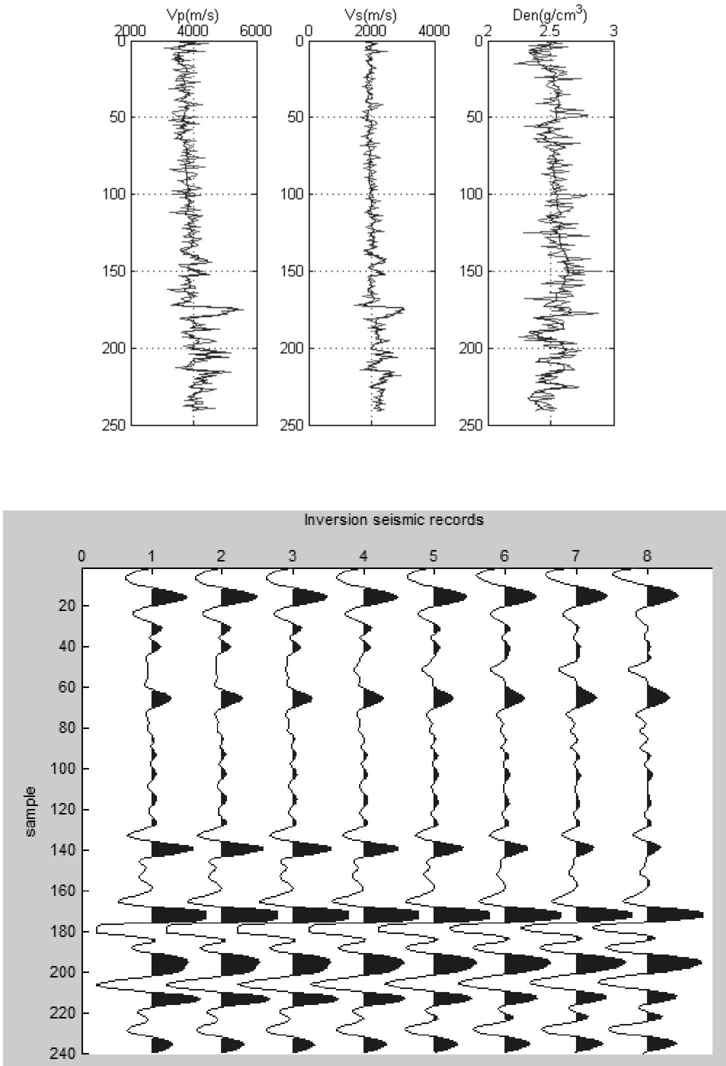

Fig. 5. Logging curves and seismic records of inversion generated by jDE

speed of the hybrid intelligent algorithm was fast, and the objective function value decreased rapidly. The simple genetic algorithm converged slowly and the jDE converged slowly. When the algorithm was in the middle and late stages, the simple genetic algorithm fell into premature convergence, the value of the objective function stayed around 0.006. Hybrid intelligent algorithm was still in the global search, and the overall effect was better than the genetic algorithm with the objective function value staying around 0.003. The error was reduced by half, but the convergence rate was obviously reduced. While the adaptive differential evolution algorithm continued the global search with convergence rate not significantly reduced, better than hybrid intelligent algorithm. The value of the objective function reached about 0.0015, and the error was reduced by half, as shown in Fig. 6.

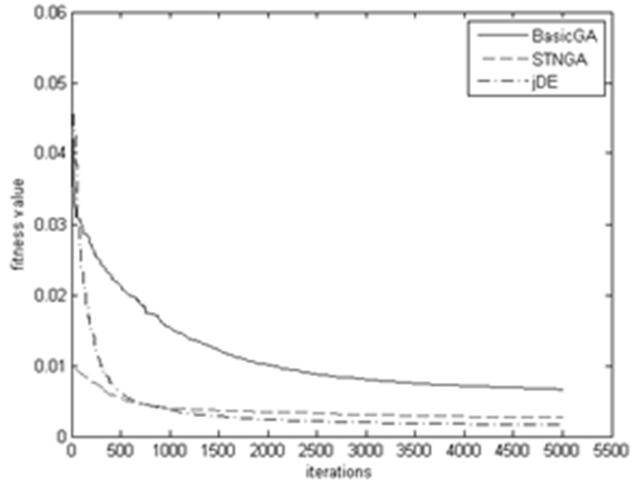

Fig. 6. Convergence curve of algorithms

It can be seen that in the early stage of the algorithm, the convergence speed was accelerated due to the adjustment of the selection strategy. In the middle and late stages, the population began to converge rapidly. Simple genetic algorithm and hybrid intelligent algorithm search remained stagnant. At this point, the jDE could dynamically update the control parameters of each individual. Therefore, it can effectively improve the diversity of the population, making the search out of the local optimum.

5. Conclusion

The main work of this paper is to combine the jDE with the AVO parameter inversion, and propose a new method to solve the inversion problem of pre-stack AVO parameters based on the inversion of the actual logging curve model and evaluation of inversion results. The experimental results show that the proposed method is better than the simple genetic algorithm and the hybrid intelligent algorithm in inversion effect and efficiency.

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