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Particle swarm optimization and its application to seismic inversion of igneous rocks

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ABSTRACT

In order to improve the fine structure inversion ability of igneous rocks for the exploration of underlying strata, based on particle swarm optimization (PSO), we have developed a method for seismic wave impedance inversion. Through numerical simulation, we tested the effects of different algorithm parameters and different model parameterization methods on PSO wave impedance inversion, and analyzed the characteristics of PSO method. Under the conclusions drawn from numerical simulation, we propose the scheme of combining a cross-moving strategy based on a divided block model and high-frequency filtering technology for PSO inversion. By analyzing the inversion results of a wedge model of a pitchout coal seam and a coal coking model with igneous rock intrusion, we discuss the vertical and horizontal resolution, stability and reliability of PSO inversion. Based on the actual seismic and logging data from an igneous area, by taking a seismic profile through wells as an example, we discuss the characteristics of three inversion methods, including model-based wave impedance inversion, multi-attribute seismic inversion based on probabilistic neural network (PNN) and wave impedance inversion based on PSO. And we draw the conclusion that the inversion based on PSO method has a better result for this igneous area.

1. Introduction

Igneous rock is characterized by its high velocity and heterogeneity, which makes it difficult to identify low amplitude structures and lithologic traps for underlying strata, and furthermore affects the process of regional oil and gas exploration. Therefore, it is very useful to conduct fine structure research on igneous rocks [1–3]. The technology of seismic inversion plays an important role in this field and model-based wave impedance inversion is one of the most traditional methods [4–10]. As a new technology, multi-attribute seismic inversion based on probabilistic neural network (PNN) has made great progress in recent years, which can be realized by four steps, including multi-attribute analysis for optimized combination of attributes, training of network, cross validation and application of PNN network for the whole work area. The method of PNN is widely used in the field of post stack seismic data inversion, and has also developed rapidly in the field of pre-stack seismic inversion. With the introduction of more new methods and new technologies like the hybrid neural network, the level of seismic inversion is also increasing continually [11–14]. Based on the integrated use of various inversion methods, a more accurate velocity field can be established, which is useful for reverse time migration imaging (RTM), data quality improvement and secondary inversion for the fine study of lithology [4–10].

Particle swarm optimization (PSO) is a new method with a simple concept and is easy to realize with fewer parameters to adjust. Since it was first proposed by J. Kennedy and R. C. Eberhart in 1995, many scholars have been attracted to the study of the algorithm. Even though it has been applied in many fields, its application in seismic inversion is still at the research stage. At present, there is no direct application of PSO seismic inversion in the mainstream of commercial software. From the very beginning of numerical simulation of PSO impedance inversion, up to now the application of PSO and its improved algorithm for actual seismic data, scholars have made some important progress. However, predecessors' numerical simulation work is usually based on simple models of twenty to thirty sampling points or just simple tests for

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anti-noise ability. Although it has been proved that PSO seismic inversion is feasible, there is still a big gap between simple theory models and complex actual data. And it is difficult for simple models to reveal the characteristics of PSO inversion for actual data [15–25].

Comprehensive numerical simulation of PSO wave impedance inversion is carried out in this paper. And the effects of different algorithm parameters and different model parameterization methods on inversion results are analyzed. At the same time, by taking the special geological models in coal field as an example, it has been proved that PSO wave impedance inversion has superiority in the recognition of seam pitchout, distinguishing the lithology of seams invaded by igneous rocks, and the detection of weak reflection coal seams. Additionally, based on the actual seismic and logging data of an igneous area from oil field, by comparing with model-based wave impedance inversion and multi-attribute seismic inversion based on PNN, we discuss the advantages and disadvantages of PSO wave impedance inversion.

2. Fundamentals

2.1. Fundamental of PSO optimization

2.1.1. Standard particle swarm optimization

The core idea of PSO optimization: firstly, design the objective function for the concrete problem and initialize the velocity parameters and location parameters of multiple independent particles randomly. The location of a particle represents parameters to be optimized for the concrete problem, and the dimension of location parameters is equal to the number of parameters to be optimized, while the velocity of particles represents the correction of each parameter to be optimized. Other parameters can be set according to the particularity of the concrete problem and their experience value. In the process of iterative optimization, the particle swarm updates the location and velocity parameters according to the historic individual optimum and global optimum. The iteration will end until it reaches the maximum of number of iterations or the error precision. And the global optimal position will be the final answer [26].

We assume that there is a model of a particle swarm: the number of particles is M, and the dimension is D. The swarm searches for the global optimum based on searching and updating of each particle. At any moment of t, the parameters of any particle i are shown as below:

Location: $x_i^t=(x_{i1}^t,x_{i2}^t,\cdots,x_{id}^t)^T$, $x_{id}^t\in[L_d,U_d]$, L_d and U_d are respectively the lower limit and upper limit of searching space.

Velocity: $v_i^t=(v_{i1}^t,v_{i2}^t,\cdots,v_{id}^t)^T$, $v_{id}^t\in[v_{\min,d},v_{\max,d}]$, $v_{\min,d}$ and $v_{\max,d}$ are, respectively, the minimum velocity and maximum velocity.

The individual optimal position: $p_i^t=(p_{i1}^t,p_{i2}^t,\cdots,p_{iD}^t)^T$, the historic individual optimal position of each particle after updating of every iteration.

The global optimal position: $p_g^t=(p_{g1}^t,p_{g2}^t,\cdots,p_{gD}^t)^T$, the historic global optimal position of particle swarm after updating of every iteration.And $1\leqslant d\leqslant D, 1\leqslant i\leqslant M$.

The location parameters at moment of $t+1$ can be calculated by Formulas (1) and (2):

$$v_{id}^{t+1}=\omega v_{id}^t+c_1r_1(p_{id}^t-x_{id}^t)+c_2r_2(p_{gd}^t-x_{id}^t) \tag{1}$$

$$x_{id}^{t+1}=x_{id}^t+v_{id}^{t+1} \tag{2}$$

In the formula, r_1 and r_2 are random numbers uniformly distributed between 0 and 1; c_1 and c_2 are called learning factors and usually $c_1=c_2=2$. ω is called inertia weight which is used for the balance between global searching and local searching. When ω is large, it is advantageous to conduct global searching. When ω is small, it is advantageous to use local searching. Generally, it is recommended to make ω change from 0.9 to 0.4 by a certain way of decreasing-linear decline being the most commonly used method. The formula of inertia weight decreased by the number of iterations is as shown below:

$$\omega=\omega_{start}-\frac{\omega_{start}-\omega_{end}}{t_{\max}}\times t \tag{3}$$

Commonly, the particle swarm optimization which uses the above decline strategy of inertia weight is called standard particle swarm optimization, also called PSO method [26].

2.1.2. Implementation steps for standard particle swarm optimization

(1) Initialization

Firstly, set basic parameters for the PSO method: the lower limit L_d and upper limit U_d of searching space, learning factor c_1 and c_2, the minimum velocity $v_{\min}$ and maximum velocity $v_{\max}$, the maximum number of iterations $T_{\max}$, the highest convergence precision ξ; Secondly, randomly initialize the location x_i and velocity v_i, and set the current position to p_i for each particle. The global optimum can be found from individual optimums. The serial number and location of the optimal particle are respectively recorded by g and p_g.

(2) Evaluation of particles

According to the objective function minimum value principle, first update the location parameter x_i and the individual optimum p_i. Then update the global optimum p_g and serial number g under the same principle.

(3) State updating of particles

First, determine the inertia weight ω according to the number of iterations. Then update the velocity and location parameters for each particle by Formulas (1) and (2). If $v_i>v_{\max}$, then $v_i=v_{\max}$. If $v_i<v_{\min}$, then $v_i>v_{\min}$.

(4) Checking for the iteration condition

If the current iteration number is larger than $T_{\max}$, or the optimal objective function value meet the highest precision ξ, then stop the iteration, and the current global optimum is the final result. Otherwise, return to step 2.

2.1.3. Commonly used inertia weight strategy

PSO-NIW: The improved non-linear dynamic inertia weight strategy (usually $k=3.0$)

$$\omega(t)=\omega_{end}+(\omega_{start}-\omega_{end})\exp\left(-k\times\left(\frac{t}{t_{\max}}\right)^2\right) \tag{4}$$

PSO-LIW: Linearly decreasing inertia weight strategy

$$\omega(t)=\left(\frac{t_{\max}-t}{t_{\max}}\right)(\omega_{start}-\omega_{end})+\omega_{end} \tag{5}$$

PSO-RIW: Random variation inertia weight strategy ($rand()$ is a random number between 0 and 1)

$$\omega(t)=0.5+\frac{rand()}{2} \tag{6}$$

PSO-TANW: Improved inertia weight strategy based on tangent function (usually $k=0.6$)

$$\omega(t)=(\omega_{start}-\omega_{end})\times\tan\left(0.875\times\left(1-\left(\frac{t}{t_{\max}}\right)^k\right)\right)+\omega_{end} \tag{7}$$