Elastic Impedance Inversion Based on Improved Particle Swarm Optimization

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Abstract. Particle Swarm Optimization has the advantages of fast convergence, simple programming and less parameters, therefore it has been widely used in solving the problems of continuous function optimization in many fields. In recent years, it begins to apply to seismic data inversion. Conventional seismic inversion adopts linear inversion methods, which strongly depend on the initial models and easily fall into local extremum. We propose an improved particle swarm optimization by adding simulated annealing, which enhances the efficiency and feasibility of the algorithm. Then we apply the improve algorithm to seismic elastic impedance inversion. After the model test of this algorithm, it is used to invert the seismic data of a certain area in Shengli Oilfield, and a number of elastic parameter profiles are obtained, which are in agreement with the actual drilling results. This method provides an effective and feasible way for the exploration and development of complex oil and gas reservoirs.

1. Introduction
The commonly used inversion methods are usually local linear iterative methods or linearization of nonlinear problems, which depend on initial models and easily fall into local extremum. In recent years, some global optimization features and good generality search algorithms, such as genetic algorithm, simulated annealing algorithm, particle swarm optimization algorithm and artificial neural network algorithm, have been widely used in seismic inversion. Among them, the particle swarm algorithm has less dependence on the initial model, less parameter settings and fast convergence speed, and can ensure the accuracy of seismic data inversion results. In order to overcome the shortcoming of the basic particle swarm optimization [1] [2] and accelerate the convergence speed, many scholars have done in-depth research on it and put forward many improvement methods. In 1998, Shi [3] proposed the inertia factor W, which made the algorithm have good global search ability in the beginning of the time and have strong local search ability in the later period of the algorithm. In 2001, Shi and Eberhart proposed the strategy of using fuzzy dynamic variable inertia factor to dynamically balance the global and local search of the particle swarm optimization algorithm. In terms of learning factors [4]; Clerc proposed the concept of contraction factor in 1999 [5] to describe a particle swarm optimization algorithm with contraction factors; Sdsgs [6] and others proposed a time-varying acceleration operator, which effectively enhanced the local search capability of the algorithm; Kennedy [7] have come to the conclusion that the best topology based particle swarm optimization algorithm is based on practical problems. In the neighborhood topology improvement, Suganthan [8] introduced the neighborhood operator in 1999. A scheme based on particle space location is proposed, which overcomes the shortcoming that the basic PSO algorithm has no obvious improvement with the increasing number of iterations in the later period of the algorithm. In the combination with other optimization algorithms, Brits [9] and others introduce the niche technology into the particle swarm
optimization algorithm; Lovbjerg [10] combines particle swarm optimization and heredity. The hybrid operator in the algorithm is combined to propose a breeding particle swarm optimization algorithm. Sun and others introduce quantum behavior into the PSO algorithm [11], and propose a quantum particle swarm optimization algorithm. Ying Gao [12] introduced chaos optimization idea into particle swarm optimization algorithm and proposed a chaotic particle swarm optimization algorithm. In this paper, a simulated annealing operator is added to the basic particle swarm optimization (PSO) algorithm, which increases the flexibility of the search process, enlarges the search range, increases the diversity of the particle swarm, and inhibits the precocious phenomenon. This method is applied to the pre stack elastic impedance nonlinear inversion of seismic exploration, and the rationality and effectiveness of the method are proved by the analysis of the theoretical model and the inversion of the actual seismic data.

1.1. Particle Swarm Optimization
The Particle Swarm Optimization derives from the group movement of birds and fish groups, which was first proposed by Dr. Kennedy and Dr. Eberhart. The mathematical description is as follows:

In the n-dimensional search space, a particle swarm is composed of M particles. \( X = (x_1, x_2, ..., x_m) \). The position of each particle represents a potential solution of the objective function. The position of the first particle is \( x_i = (x_{i1}, x_{i2}, ..., x_{im}) \) The velocity of its movement in space can be expressed as \( v_i = (v_{i1}, v_{i2}, ..., v_{in}) \), the optimal position of its experience is recorded as \( p_{best} = (p_{i1}, p_{i2}, ..., p_{in}) \), and the optimal position that can be searched by the whole particle swarm is recorded as \( g_{best} = (g_1, g_2, ..., g_n) \). The velocity and position of each particle is updated according to the following equation

\[
\begin{align*}
v_{id}(t+1) &= wv_{id}(t) + c_1r_1(p_{id}(t) - x_{id}(t)) + c_2r_2(g_{id}(t) - x_{id}(t)) \\
x_{id}(t+1) &= x_{id}(t) + v_{id}(t+1) \\
&1 \leq i \leq m \quad 1 \leq d \leq n
\end{align*}
\]

(1)\(\)

Among them: \( w \) is inertial weight factor; \( c_1 \) and \( c_2 \) are accelerating factor, they are all positive constant. \( c_1 \) is the step to adjust the direction in which a particle flies to its best position. \( c_2 \) is the step at which particles travel to the best position overall situation. \( t \) is the current number of iterations. \( r_1 \) and \( r_2 \) are the random number between 0 to 1.

\[
\begin{align*}
v_{id} &= V_{max} \\
v_{id} &> V_{max} \\
v_{id} &= -V_{max} \\
v_{id} &< V_{max}
\end{align*}
\]

(3)

An upper limit \( V_{max} \) can be set to ensure that particles do not miss the optimal solution because the velocity is too high. According to equation (3), the velocity and initial position of particles are randomly generated, and then iterated according to equation (2) and equation (3) until a suitable solution is found. Particle swarm optimization (PSO) is a kind of efficient search method, which is convenient to realize, fast convergence speed and less parameter setting, but premature convergence and easy to fall into local extremum are the main shortcomings of PSO.

1.2. Stochastic Particle Swarm Optimization Algorithm with Simulated Annealing Operator
In the above basic particle swarm optimization algorithm, when \( w = 0 \) the evolution equation of particles becomes the equation (4).

\[
x_{id}(t+1) = x_{id}(t) + c_1 r_1(p_{id} - x_{id}(t)) + c_2 r_2(g_d - x_{id}(t))
\]

(4)\(\)
Compared with PSO, the evolution equation can enhance the local search ability, but weaken the
global search ability. If $x'_j = p_j = g_j$, the particle will stop searching. In order to improve the global
search ability of equation (4), the historical optimal value of the particle swarm can be preserved,
and the particle can be randomly regenerated in the search space, while the other particles I
continue to search according to equation (4). Then there is:

$$p_{j\delta} = x_{j\delta} (t+1)$$ (5)

$$p_{d\delta} = \begin{cases} p_{d\delta}, & f(p_{d\delta}) < f(x_{d\delta}(t+1)) \\ x_{d\delta}(t+1), & f(p_{d\delta}) \geq f(x_{d\delta}(t+1)) \end{cases}$$ (6)

$$g_d = \arg\min \{ f(g_d), f(g_d') \}$$ (7)

$$g'_d = \arg\min \{ f(p_{d\delta}), i = 1, S \}$$ (8)

According to the equation (4) and equation (5), when the particle $j$ is located at the historical optimum
position, Cannot update position according to equation (4), the random generation will continue in the
search space, and the other particles will be searched according to the equation (4) after updating $p_j$, $g_d$. When $g_d \neq p_j \delta$. If $g_d$ is not updated, Update position all particles’ positions are updated
following up equation (4); b. If $g_d$ has been updated, there is a particle ‘k’ in the search space to
make $x_j(t+1) = p_{j\delta} = g_d$. Particle ‘k’ will stop searching. And then re-generate it randomly in the
search space. The rest of the particles will continue to search according to equation (4) after updating
$p_j, g_d$. In this way, the global search ability of the algorithm is enhanced. This algorithm is called
stochastic particle swarm optimization (SPSO). In order to achieve the optimal solution with high
probability; the author proposes a stochastic particle swarm optimization algorithm with simulated
annealing operator. Take the current historical optimal position $g_d$ as the initial state and select the
initial temperature $T = T_0$. Classical annealing process $T_k = a^{\frac{1}{T_0}}$, according to equation (9) the next
state is generated:

$$x_j(t+1) = x_j(t) + \eta \xi$$ (9)

$\eta$ is a perturbed amplitude parameter; $\xi$ is random variable for a subordinate Cauchy
distribution or a normal distribution. Count $f'_j = f(x'_j(t+1))$, $f_j = f(x_j(t))$, $\Delta f = f'_j - f_j$

$$x_j(t+1) = \begin{cases} x_j(t+1), & \min \{ 1, e^{-\eta / \xi} \} \geq \gamma_j \\ x_j(t), & \text{otherwise} \end{cases}$$ (10)

$\gamma_j \in [0,1]$ It is random variables with uniform distribution. The simulated annealing method itself has
good global convergence. Therefore, the proposed method can generate particles $j$ and update the
state according to equation (9) and equation (10), which will not have a negative effect on the global
convergence of the stochastic particle swarm optimization (RPSO) algorithm.

2. Model Verification

Elastic impedance inversion can be regarded as the problem of function optimization for extreme
value, that is to say, the reflection coefficient sequence $r(t)$ of each corner gather is required to be
taken to minimize the error function $Fr$ between the convolution of angle wavelet $w(t)$ and the actual
seismic record, then the optimization objective function is equation (11).

\[ F(r) = \left\| S(t) - w(t) \ast r(t) \right\| \rightarrow \min \]

(11)

The logging curve containing 100 time samples is used as the data model and the sampling interval is 1 ms. The parameters of the hybrid particle swarm optimization algorithm are as follows: population size \( m = 30 \); inertia factor \( w = 0.1 \); learning factors \( c_1 = c_2 = 1.8 \); \( x_{\min} = -1, x_{\max} = 1, v_{\max} = 1 \), the error requirement is less than 0.000001; the initial temperature is \( T_0 = 100000 \) and the coefficient of cooling is \( a = 0.95 \) by classical annealing method.

The elastic parameters such as P-wave impedance, S-wave impedance, density, P-wave velocity and S-wave velocity are calculated. It can be seen from figure 1 that the obtained elastic parameter curves are in good agreement with the log data curves.

![Figure 1. Comparison of the inversed elastic parameters curves (dashed lines) and the original logging curves (solid lines)](image)

3. Application Example and Effect Analysis

The elastic impedance inversion based on improved particle swarm optimization (PSO) is carried out by selecting 2D data from a certain area in Shengli Oilfield.

According to the characteristics of these three parameters, the location of the oil-bearing zone can be determined. Figure 2 make use of the elastic impedance inversion method proposed by the author to generate profiles of the above three parameters. The location of the oil-bearing reservoir indicated by the ellipse in the figure is about 2400 ms, and the drilling in the position of CDP385 (vertical dashed line in the picture) is also well matched.
Figure 2. \( V_r/V_s \) section with da21 well (vertical line denotes the well of da21 and white ellipse denotes the reservoir)

4. Conclusion
In this paper, particle swarm optimization (PSO) algorithm is applied to elastic impedance inversion. The convergence rate and precision are improved by random perturbation of particles generated by each generation of evolution and addition of simulated annealing operator. The well logging data are used to verify and apply to the elastic impedance inversion of the actual data of a certain working area in Shengli Oilfield. The attribute profile extracted by this method can reflect the reservoir characteristics, which is consistent with the logging results. It shows that the elastic impedance inversion method based on improved particle swarm optimization algorithm is effective.

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