Virtual well-logging curves construction using a genetic algorithm and its application to reservoir inversion

Introduction

With the rapid progress of oil and gas exploration and development, seismic detailed interpretation for the geological structure of the reservoirs becomes more and more important. The information provided by the well data is commonly considered as reliable. However, due to the huge drilling costs, the well-logging information is limited or even missing in some areas, resulting in inaccurate reservoir interpretations. To tackle this problem, we use a genetic algorithm (GA) to construct virtual well-logging curves based on pre-stack angle gathers, and apply this information to constrain subsequent inversion process, which can combine the advantages of high vertical resolution of well-logging data and good horizontal prediction of seismic data. The results show that the virtual well curves constructed by the proposed method combined with the original well data as a constraint condition can produce a higher-precision initial model, which is more consistent with the actual geological conditions. Finally, it is feasible to improve the accuracy of seismic reservoir inversion results [1].

Method

The pre-stack seismic data describes the amplitude-variation-with-offset (AVO) information for subsurface reflectors, and the AVO inversion result based on the pre-stack seismic data has a higher resolution. However, the AVO inversion based on the Zoeppritz equation is essentially a nonlinear problem, the approximated linear inversion method is easily to fall into local minimums and largely depends on the initial model. To mitigate this problem, one can use a nonlinear algorithm with global search to perform inversion, which can make the inversion result converge to the true solution as much as possible. There are many optimization algorithms with global search performance, such as particle swarm optimization (PSO) algorithm and simulated annealing optimization (SA) algorithm. However, the PSO algorithm cannot accurately solve the discrete problem and combinatorial optimization problem [2]. The SA algorithm needs to reduce the cooling speed in the application process, so the convergence speed is relatively slow. Compared with these two methods, the genetic algorithm (GA) has a good performance. The GA method was proposed by J. Holland in the 1970s. It is a stochastic global optimization algorithm developed based on the evolutionary laws of biological theory, and the algorithm can traverse all the solutions in a space to find the optimal value. The theoretical basis is easy to be understood and numerically implemented, and the algorithm has the advantages of parallelism and global search. The genetic algorithm searches for the optimal solution in the solution space by copying, recombining, and mutation [3].

The detailed workflow can be summarized as the following steps:

1. Data preparation: The original seismic records are pre-processed by denoising, true amplitude recovery, and angle gathers conversion to obtain pre-stack angle gathers Seis. We use velocity analysis to obtain the layer velocity model and calculate the initial model parameters $V_p, V_s, \rho$, in which $V_p, V_s, \rho$ are the P-wave velocity, S-wave velocity, and density parameters, respectively;
2. Select the objective function of the inversion algorithm $O_{specs}$ and inversion constraint accuracy $\varepsilon$ ;
3. Use commercial software HRS to inversion the three parameters of certain CDP locations to determine the search range and interval of geological model parameters, and perform integer coding the randomly generate the initial population $E_0$ ;
4. Use the equation of Zoeppritz equation to simulate the synthetic seismic records $Syn_i$ based on $E_0$ , and calculate the objective function value using $Syn_i$ and $Seis_j$ , where the objective function (Journé et al., 2019) is:

$$Objects_i = \sum_j \left| \frac{Seis_j - Syn_{ij}}{N_{dt}} \right| , \ i = 1, \cdots, n \quad j = 1, \cdots, m$$

(1)

where, $n$ represents the number of population samples, $m$ represents the number of individuals in the random model, $N_{dt} = dt \times N_o$ , $dt$ represents the number of time sampling points for each seismic trace,
and \( N_w \) represents the number of angle in the angle gathers. \( S e i s_j \) represents the pre-stack seismic data of the \( j \)-th random model, and \( S y n_j \) represents the synthetic seismic records of the \( i \)-th population sample as well as its \( j \)-th random model;

(5) Update \( E_i \) via copying, recombining, and mutation, count \( i = i + 1 \);

(6) At last, the moderate function value \( \text{Fitness}_i \) calculated by \( \text{Objects}_i \) is incorporated to verify the convergence of our proposed method:

\[
\text{Fitness}_i = \frac{\exp(-\text{Objects}_i/\sigma)}{\sum_i \exp(-\text{Objects}_i/\sigma)} 
\]

Where, \( \text{Objects}_i \) represents the objective function value of the \( i \)-th population sample; \( \sigma \) represents the variance of the value of the group objective function;

(7) When \( \text{Fitness}_i < \varepsilon \) in step (4), save model parameters \( V_P, V_S \) and \( \rho \); otherwise, return to the step (5) \([4]\);

(8) The well data obtained by pre-stack inversion based on genetic algorithm and the original well data are interpolated together to construct a high-precision initial model, and use this to constrain the subsequent nonlinear iterative optimization inversion process.

**Examples**

In order to verify the effectiveness and feasibility of our method, we show the use of field seismic data to carry out a genetic algorithm-based nonlinear global optimization inversion method.

![Figure](image)

*Figure 1* (a) shows the fitness of the virtual well curves calculated with the genetic algorithm
compared with the actual logging curves. The solid red line in the Figure is the three-parameter curve of the actual log, and the blue dotted line is the three-parameter curve of the virtual well obtained by the genetic algorithm. The black dotted line is the search window. (b) shows the comparison between the theoretical simulation seismic record and the three parameters calculated forward simulation angle gathers seismic record. (c) shows the trend of the convergence function of the algorithm.

In Figure 1 (a) the correlation coefficient between the virtual well curve and the real log curve can be calculated and analyzed. The correlation coefficient of P-wave velocity is 0.9362, the correlation coefficient of S-wave velocity is 0.8594, and the correlation coefficient of density is 0.6523. In addition, the error profile value in Figure 1 (b) is small. It is proved that the virtual well curve has higher quality, and indirectly verifies the feasibility of this method. In Figure 1 (c) the value of the objective function gradually decreases and the function converges with iterations increasing. During the first 300 iterations, the convergence rate is very fast. When the number of iterations is greater than 300, the convergence rate gradually slows down, which indirectly proves the stability of the GA inversion.

The actual seismic area size is 875.78 km², we intercepted 104.85 km² of seismic data for technical testing. The Xline range is 5076 ~ 6305, and the Inline range is 2096 ~ 2642. There are only two wells in the range. The position of Well1 is Xline = 5543, Inline = 2203, the position of Well2 is Xline = 5595, Inline = 2493. The distance between the two wells is 5 km. Obviously, it is not enough to construct the initial model by interpolation between these two wells as a constraint condition for the subsequent inversion process, and the inversion result cannot reach the desired accuracy. In order to improve the accuracy of the inversion method, the specific work of this paper is to use genetic algorithm to construct virtual well3 at Xline = 5625, Inline = 2493 and well4 at Xline = 5660, Inline = 2493. The two virtual wells and the two known well1 and well2 in the actual work area are common used to establish a reliable initial geological model. In order to facilitate the comparison of effects, some seismic data are intercepted for testing. Only the stratigraphic profiles in the work area with Xline of 5500 ~ 5700, Inline = 2493, and time of 2.8 ~ 3.3 s are shown. Due to the large number of parameters in the inversion results, we only shows the comparisons for P wave velocities.

Figure 2 (a) shows the initial model of P-wave velocity interpolated by the first and second wells in the actual working area. (b) shows the high-precision initial model built after adding two virtual wells. (c) shows the P-wave velocity inversion result obtained by AVO inversion with the initial velocity model in (a) as the constraint. (d) shows the inversion result using the same inversion method.
but with the initial velocity model of (b) as the constraint.

The comparison of figure 2 (a) and figure 2 (b) shows that after adding two virtual wells, some small structures appear in figure 2 (b), the quality of the profile has been improved, and construct a high precision velocity initial model. Comparing the outline of Figure 2 (c) and Figure 2 (d), the event becomes thinner, the continuity is better, the contact relationship is clearer, the results are easier to interpret, and the inversion result is more accurate. It can be seen from figure 3 (a) and figure 3 (b) that the two profiles fit well.

![Figure 3](image)

**Figure 3** (a) shows the profile of the actual post-stack seismic record, while (b) shows the profile of post-stack seismic records obtained by forward-modeling of the high-precision initial velocity model.

**Conclusions**

Pre-stack seismic inversion based on genetic algorithm can construct virtual well curves that conform to the characteristics of actual formation changes. Constructing multiple virtual wells covering the target reservoir in the work area, together with the known well data in the work area as a constraint condition, can build a more refined initial model to improve the resolution and accuracy of the reservoir inversion results.

**References**


