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# Broadband Constraint Based Simulated Annealing Impedance Inversion

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**Abstract**

In order to enhance the accuracy and improved the resolution of the inversion result in gas hydrate exploration, this paper proposed a new inversion method. By introducing broadband constraint based simulated annealing impedance inversion, the new method allows for a more extensive search for the optimal solution and is more efficient than exhaustive enumeration in solving global optimization problems. Compared to other inversion solutions as constraint sparse spike inversion and model based inversion, the new method not only solved the global optimization problems, but also improved the resolution of the profiles and enhanced the inversion accuracy, which is helpful to the later interpretation.

## 1. Introduction

Seismic wave impedance inversion is an effective means for reservoir prediction as there's a commendable correspondence between wave impedance and hydrocarbon reservoir. Impedance inversion is actually a physical parameter impedance of eliminating the influence brought by seismic wavelet and maintaining the coefficients which are further used to calculate the physical changes of the strata.

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There are many ways of impedance inversion. The most commonly adopted is generalized linear inversion which has higher inversion accuracy. However, during the inversion, the high-frequency noise can bring great influence on solving the morbid equations; even regularization factors are added, the influence can't be eliminated. So, this paper proposed broadband constraint based simulated annealing impedance inversion.

Simulated annealing algorithm originated from the simulation of annealing process in metallurgy, is a generic probabilistic metaheuristic for the global optimization problem of locating a good approximation to the global optimum of a given function in a large search space, especially when the search space is discrete [1].

## 2. Simulated Annealing Algorithm and Its Application in Gas Hydrate Exploration

***2.1 Principle of Simulated Annealing Algorithm.*** Simulated annealing algorithm uses a set of parameters named cooling schedule to control its process and obtain the global optimum solution of the combinatorial optimization problem when the control parameter $t$ is "cooling" and tends to zero. Here, a solution $i$ and its objective function of the optimization problem are corresponding to a microstate $i$ and its energy $E_i$. The descending control parameter $t$ is used to describe the temperature $T$ in the process of annealing of the material. Simulated annealing algorithm is an adaptation of the Metropolis-Hastings algorithm [2]. As for each value of $i$, the iteration of "generating new solution- judging- accept or abandon " is ongoing until reach the "balance point" under that temperature.

During the process of simulated annealing algorithm, if the new point's energy $f'$ is a small value compared to energy $f$ of a randomly selected point in the model space, i.e., $f' - f = \Delta f < 0$, the new model will be accepted unconditionally; if the $f'$ is a large value, i.e., $f' - f = \Delta f > 0$, the acceptance probability of the new model is $p = \exp(\Delta f / T)$. Here, $T$ is the controlling parameter. As for a fixed temperature, the test of acceptance process will be repeated until the objective function is constant. As the acceptance probability of heating is always greater than zero, the operator can always reach to the global optimum [3].

***2.2 The specific steps of simulated annealing algorithm are as follows:***

Step 1: Specify cooling schedule parameter which include the initial value $t_0$ of the controlling parameter $t$, attenuation function, final value and Mapkob chain length $L_k$; specify initial solution $X_0$ of the iteration $f(X_0)$.

Step 2: When $t = t_k$, carry out $L_k$ times of searches according to the following method:

- Generate random vector $Z_k$ (as for continuous variable) or random offset $m'$ (as for discrete variable) according to property of the current solution $X_k$, thereby obtain the new test point in the neighbourhood.

$$X_k = \begin{cases} X_k + Z_k, & \text{continuous variable} \\ X(m + m'), & \text{discrete variable} \end{cases} . \quad (1)$$

As for discrete variable, X is the value sequence and m is the discrete location of the current solution.

- Generate a random number G that uniformly distributed on (0, 1), calculate the transition probability P that corresponding to Metropolis

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acceptance rule under current iteration point $X_k$ and temperature $t_k$ [2].

$$P = \begin{cases} 1, & f(x_k^{'}) \le f(x_k) \\ \exp\left[\dfrac{f(x_k) - f(x_k^{'})}{t_k}\right], & f(x_k^{'}) > f(x_k) \end{cases} . \tag{2}$$

If difference of objective function is less than zero, i.e., $\Delta f < 0$, the new solution will be accepted, otherwise, reserve the current solution.

- If the test searches is less than $L_k$, return to step 1, otherwise go into step 3.

Step 3: The current solution will be used as approximate optimal solution if the termination condition of the iteration is satisfied, and then the algorithm is completed; otherwise, go into step 4.

Step 4: Generate new temperature controlling parameter $t_{k+1}$ and Mapkob chain length $L_{k+1}$ according to the given temperature attenuation function, and return to step 2 for the balance point optimization of the next temperature point.

Simulated Annealing Algorithm for Impedance Inversion. The propagation of the seismic wave in the transverse homogeneous acoustic media is an approximate convolution model, as shown in Eq. 3.

$$S(t) = \left[R(\tau)W(t-\tau)\right]d\tau . \tag{3}$$

Here, $S(t)$ is two-way travel time seismic trace; $W(t)$ is seismic wavelet; $R$ is seismic reflection coefficient sequence. Typically, seismic wavelet is unknown and can be obtained through various methods. It should be noted that the convolution model indicates the relation between post-stack seismic record and unknown model parameters, such as velocity, density and impedance. However, the actual seismic data is affected by geometrical attenuation, viscoelastic absorption, wave dispersion, as well as the loss of converted wave and multiple reflections. Thereby, proper corrections are needed to the actual seismic data.

In the seismic wave inversion, low frequency wave impedance constraint can reduce the non-uniqueness of the solution of the inversion. Here, we can adopt L1 model to establish objective function, in which, the first item is the absolute error between the actual seismic trace and model seismic trace, the second item is the absolute error between prior wave impedance and model wave impedance that enables inversion result close to the variation trend of the low frequency wave impedance. The objective function is shown in Eq. 4.

$$\Delta f = \omega_1 \frac{\sum_{i=1}^{n}\left|S_o^i - S_m^i\right|}{\sum_{i=1}^{n}\left|S_o^i\right|} + \omega_2 \frac{\sum_{i=1}^{n}\left|I_p^i - I_m^i\right|}{\sum_{i=1}^{n}\left|I_p^i\right|} . \tag{4}$$

Here, $S_o^i$ refers to the actual seismic data; $S_m^i$ is the synthetic seismogram; $I_p^i$ is priori wave impedance and $I_m^i$ is model wave impedance. The amplitude of the seismic wave must be well matched with the synthetic seismogram generated by logging curves and the objective function must be normalized before the inversion. At this moment, the weighting factor is 1.

The optimization process requires a fitting standard to estimate the quality of each test model. The one that can make the objective function reach to global optimum is the best model. Various constraints can be added into the model, this is

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essential to reduce the non-uniqueness of the solution of the inversion.

## 3. Experimental Results Analysis

In order to examine the effect of the new method proposed, we designed a series of inversion experiments. The seismic data is acquired from a target gas hydrate exploration area in the South China Sea. Broadband constraint based simulated annealing inversion converts the known conditions into specific constraints, so as to control the inversion process. The designed inversion process is shown in Figure 1.

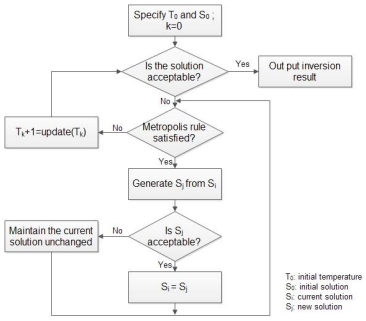


Fig. 1 Process of broadband constraint based simulated annealing impedance inversion

In order to reduce the non-uniqueness and enhance the stability of the solution, priori impedance information that adopted pseudo-logging curves can be added into the algorithm as constraint item of the objective function. The constraint item can compensate the missing low frequency information of the band-limited seismic data. The inversion is called pseudo-logging inversion if the constraint item is adopted or inversion without well control if not adopted.

The initial model and seismic wavelet used in broadband constraint based simulated annealing inversion are the same as in some other inversion methods, such as constraint sparse spike inversion and model based inversion.

Here, we carried out two different inversions to the data acquired from the target area, i.e., pseudo-logging impedance and impedance without logging control. As for the first inversion, we can obtain pseudo-logging impedance result through simulated annealing algorithm that adopted initial model; as for the second inversion which is less dependent on pseudo-logging data and more dependent on seismic data, we can directly obtain the inversion result through the calculation of the initial model. Figure 2 and Figure 3 showed the profiles of these two inversions of the test line in the target area.

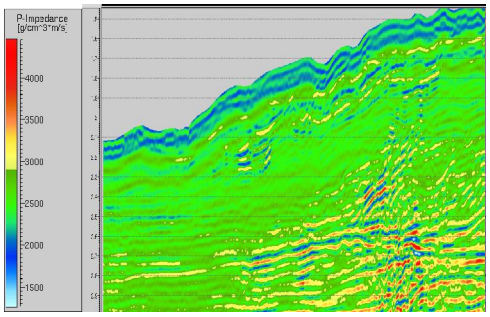


Fig. 2 Profile of pseudo-logging constraint impedance of the test line

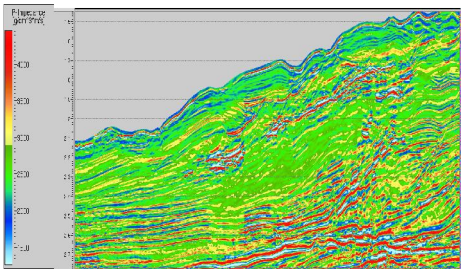

Fig. 3 Profile of the impedance without logging control of the test line

As can be known from the simulated annealing impedance inversion results, profile with logging data (Figure 2) reflected the high impedance of the possible gas hydrate reservoir and the low impedance of the free gas; while the profile without logging data (Figure 3) possesses higher vertical resolution and can reflects the relative relation

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between the gas hydrate reservoir and the upper and lower strata, and thus can more finely reflect the occurrence and spatial distribution of the gas hydrate.

## 4. Conclusion

This paper introduced the simulated annealing algorithm into impedance inversion in gas hydrate exploration, where simulated annealing is more efficient than exhaustive enumeration. Broadband constraint based simulated annealing inversion allows for a more extensive search for the optimal solution. Compared to constraint sparse spike inversion and model based inversion, it not only solved the global optimization problems, but also enhanced the accuracy and improved the resolution of the inversion results under the constraints.

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