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A new parallel simulated annealing algorithm for 1.5D acoustic full-waveform inversion

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Summary

Full-wave inversion (FWI) based on deterministic optimization methods is an appealing tool to detect the physical properties of the subsurface media, and increasing successful examples have been reported. However, the deterministic optimization FWI is highly model-dependent, a good enough starting model is needed. To solve this problem, some researchers resort to the stochastic global optimization methods that have shown the potential to alleviate the suffering of the model-dependent problem in FWI. However, stochastic global optimization needs to solve a great number of forward problems. This is dramatically computationally expensive for the wave-equation-based FWI. In our study, we use a heuristic global optimization algorithm, the very fast simulated annealing (VFSA) algorithm, to implement the constant-density acoustic FWI. To save computational time, we develop a new parallelization VFSA, in which the serial structure of VFSA is changed to some degree. Instead of updating the model parameter one by one in the same thread in a conventional serial VFSA, the parallel VFSA updates the N model parameter separately on N threads, in which the maximum efficient processor number is N. Since performing a 2D VFSA FWI directly without using any parameterization to reduce parameter number (dimension) is still prohibitive, we test our method on a 1.5D acoustic model. We use both an unbiased starting model crossing the true model and a biased starting model far away from the true model with the depth increase to show the feasibility of our method.

Method

Very fast simulated annealing (VFSA) (Ingber and Rosen, 1992), also known as the adaptive simulated annealing (ASA) (Ingber, 2000), is a popular method in the simulated annealing (SA) family (Metropolis et al., 1953; Kirkpatrick et al., 1983; Geman and Geman, 1984; Cerby, 1985; Pincus, 1970) which mimics the annealing process of a physical crystallization. During the process, the temperature of the heated material is lowered gradually, thus the system energy is reduced. Until the system reaches the equilibrium state, namely the system energy becomes stable, this annealing process is finished. To crystallize (i.e., reach the global minimum of the energy function) successfully and quickly, a suitable annealing schedule is necessary. Too fast annealing could lead to crystallization failure, while too slow annealing will increase the computational cost. Especially for FWI using wave equation (Lailly et al., 1983; Tarantola, 1984)), the computation cost may raise to an unacceptable level.

VFSA is a heuristic stochastic global optimization method. A new candidate model $\mathbf{m}_{k+1}^{i}$ in the parameter i at temperature k is given by a Cauchy distribution expressed as

$$\mathbf{m}_{k+1}^{i} = \mathbf{m}_{k}^{i} + y^{i}(\mathbf{m}_{\max}^{i} - \mathbf{m}_{\min}^{i}), \quad (1)$$

$$y^{i} = \mathrm{sgn}(u^{i} - 0.5)T_{k}\left[(1 + 1/T_{k})^{|2u^{i}-1|} - 1\right], \quad (2)$$

$$T_{k} = \alpha T_{k-1}, \quad u^{i} \in U(0,1), \quad (3)$$

where, α is less than 1, depends on the complexity of the inverse problem, e.g., 0.9 for an easy problem and 0.99 for a tough one. Next, using Metropolis criterion to accept or reject the new candidate model. Acceptance probability

$$p = \begin{cases} 1 & if \quad E(\mathbf{m}_{k+1}) < E(\mathbf{m}_{k+1}) \\ \exp(-\dfrac{E(\mathbf{m}_{k+1}) - E(\mathbf{m}_k)}{T_k}) & if \quad E(\mathbf{m}_{k+1}) \geq E(\mathbf{m}_{k+1}) \end{cases}, \tag{4}$$

where $E(\mathbf{m})$, here, is an energy function given by

$$E(\mathbf{m}) = \frac{\| \mathbf{d}_{obs} - \mathbf{d}_{syn}(\mathbf{m}) \|_1}{\| \mathbf{d}_{obs} \|_1}, \tag{5}$$

$\mathbf{d}_{obs}$ is the observed shot gather seismic data, $\mathbf{d}_{syn}(\mathbf{m})$ is the synthetic data with wave equation and the current model $\mathbf{m}$. There multisource are applied to release the computational. In VFSA FWI, we do not have the trouble of crosstalk artifacts involving multisource shot gathers. Thus, directly using the multisource shot gather data is safe.

The performances of most present parallelism methods are highly problem-dependent, thus design a suitable parallel SA for FWI (1.5D acoustic FWI in our work) is necessary. In this paper, we design a new parallel scheme based on a single-chain VFSA, in which each parameter is updated simultaneously rather than sequentially in a conventional VFSA with no parallelization. Instead of updating the model parameter one by one in the same thread in a conventional serial SA, this parallel VFSA updates the N model parameter separately on N threads. In this parallel VFSA, the maximum effective number of processors is the same as that of model parameters.

1.5D ACOUSTIC MODEL EXAMPLE

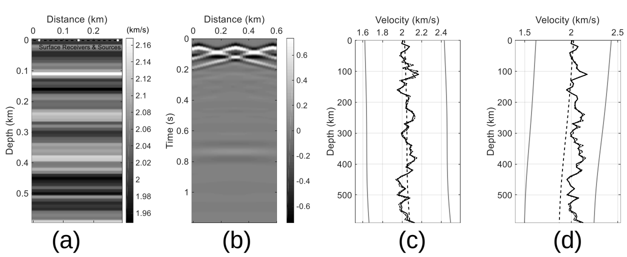

Figure 1: (a) Ture velocity model, and acquisition geometry. (b) Multisource observed data. (c) and (d) are, respectively, inverted results (dash-dot lines) using unbiased and biased initial models (dash lines). The solid lines are true models, the gray lines are bounds.

Figure 1a-d show a 1.5D acoustic model example to demonstrate the feasibility of our new method, from which we observed that the inverted results are very close to the true models for both unbiased and biased initial models. These also discover the potential of the new VFSA method to solve the problem that FWI relies much on the initial model.

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