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Improved estimation of P-wave velocity, S-wave velocity, and attenuation factor by iterative structural joint inversion of crosswell seismic data

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ABSTRACT

We present an iterative joint inversion approach for improving the consistence of estimated P-wave velocity, S-wave velocity and attenuation factor models. This type of inversion scheme links two or more independent inversions using a joint constraint, which is constructed by the cross-gradient function in this paper. The primary advantages of this joint inversion strategy are: avoiding weighting for different datasets in conventional simultaneous joint inversion, flexible for incorporating prior information, and relatively easy to code. We demonstrate the algorithm with two synthetic examples and two field datasets. The inversions for P- and S-wave velocity are based on ray traveltime tomography. The results of the first synthetic example show that the iterative joint inversion take advantages of both P- and S-wave sensitivity to resolve their ambiguities as well as improve structural similarity between P- and S-wave velocity models. In the second synthetic and field examples, joint inversion of P- and S-wave traveltimes results in an improved Vs velocity model that shows better structural correlation with the Vp model. More importantly, the resultant V_P/V_S ratio map has fewer artifacts and is better correlated for use in geological interpretation than the independent inversions. The second field example illustrates that the flexible joint inversion algorithm using frequency-shift data gives a structurally improved attenuation factor map constrained by a prior V_P tomogram.

1. Introduction

Due to data deficiency and complex characteristic of geological system, e.g. multiple fluids in the reservoir, single geophysical model might be difficult to characterize the geological target fully. For example, compressional waves are very sensitive to gas-saturated rocks while shear waves are not. Attenuation is potentially more sensitive than velocity to the amount of gas in a rock (Winkler and Murphy, 1995). The ratio of Vp/Vs is more sensitive to changes of fluid type than Vp or Vs separately (Dvorkin et al., 1999; Hamada, 2004). It is also believed that attenuation factor is closely related to permeability (Pride et al., 2003). We can see that different geophysical models tend to reflect complementary characters of reservoir. It is natural to combine several types of geophysical data collected over the same reservoir region to reduce ambiguity in inversion results, leading to more reliable models for reservoir characterization.

A type of joint inversion refers to combining several different types of geophysical datasets in a single inversion algorithm and then simultaneously or iteratively solving a least-squares problem (Vozoff and Jupp, 1975; Haber and Oldenburg, 1997; Julia et al., 2000; Gallardo and Meju, 2003). Simultaneous joint inversion approaches have been successfully applied for different geophysical data to provide improved geophysical models (e.g., Gallardo and Meju, 2004; De Stefano, 2007; Linde et al., 2008; Doetsch et al., 2010; De Stefano et al., 2011; Gao et al., 2012; Lelievre et al., 2012). However, coupling two or more datasets in a single inversion still face some difficulties, especially large-scale problem: first, the huge coupled Jacobian and/or Hessian matrices for the different data inversions have to be computed and/or stored for simultaneous use (Hu et al., 2009); second, the determination of suitable relative weighting between different objective functions can be challenging (Gallardo and Meju, 2007; Moorkamp et al., 2011).

In this paper, we discuss an alternative approach to simultaneous joint inversion for the tomography problem that is quite similar to the ones of Hu et al. (2009) and Heincke et al. (2010). The iterative joint inversion couples independent inversions through iterations with a cross-constraint term. At every iteration, we still run an independent inversion by minimizing an objective function with the additional cross-constraint term. The presented approach overcomes the memory issue and the determination of relative weighting of different data sets. The cross constraint could be a direct parameter relation or a structural link. A direct parameter relation for different models based on the empirical or rock-physics relations (e.g., Carcione et al., 2007) may be limited in

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some specific places. Instead, we implement a structural link—the cross-gradient function—which measures the structural similarity between the different models instead of the direct parameter relation (Gallardo and Meju, 2003; Zhu and Harris, 2011; Um et al., 2014).

Another advantage of the iterative joint inversion algorithm with the cross-gradient structural constraint is its flexibility to incorporate prior models into the independent algorithms. For example, a prior lithologic map (e.g., from reflection-migrated images) could be applied to constrain other parameters in the cross-gradient function. This is easy to implement as an additional regularization term in an independent inversion within a single unknown, but it is difficult to use for multiple unknowns, whose unknowns may not be on the same order of magnitude (e.g., velocity and resistivity).

We begin by presenting a flexible iterative joint inversion framework that allows us to test different geophysical datasets. We then give an overview of the different parts of the joint inversion framework: the objective function definition, the cross-gradient function, and the determination of regularization weights. We test the algorithm with two synthetic examples for jointly inverting V_p and V_s models. Finally, we apply the approach to two seismic cross-well field datasets acquired at the west Texas for reservoir characterization.

2. Methodology

The inverse problem is formulated as an optimization that minimizes an objective function Φ, which combines a measure of data misfit, Φ_d, a regularization measure Φ_m:

$$\min\Phi(\mathbf{m}) = \Phi_d(\mathbf{m}) + \lambda\Phi_m(\mathbf{m}), \tag{1}$$

where the model vector $\mathbf{m}$ is a spatial function m(x,y,z), and λ is a regularization parameter, which is used to adjust contributions for data misfit from the model regularization term and the constraint function.

The objective functions of the iterative joint inversion of two datasets with a cross constraint $\psi_{cc}(\mathbf{m}_1,\mathbf{m}_2)$are defined as

$$\begin{aligned}\Phi_1 &= \Phi_d(\mathbf{m}_1) + \lambda_1\Phi_m(\mathbf{m}_1) + \beta_1\psi_{cc}(\mathbf{m}_1,\mathbf{m}_2),\\ \Phi_2 &= \Phi_d(\mathbf{m}_2) + \lambda_2\Phi_m(\mathbf{m}_2) + \beta_2\psi_{cc}(\mathbf{m}_1,\mathbf{m}_2),\end{aligned} \tag{2}$$

where $\mathbf{m}_1$ and $\mathbf{m}_2$ denote two models for two corresponding datasets. In such an iterative joint inversion, we still run two inversions separately. In each independent inversion, the cross constraint is functional as a new regularization and includes complementary information from a joint model during iterations. The coefficient β controls the influence from other models on the solution through the cross constraint. Through the constraint $\psi_{cc}(\mathbf{m}_1,\mathbf{m}_2)$, two independent inversions in Eq. (2) exchange information (e.g., geologic structure) during iterations.

The data misfit Φ_d and the regularization terms Φ_m are written as

$$\Phi_d(\mathbf{m}_i) = \left\|\mathbf{W}_d\left(\mathbf{G}(\mathbf{m}_i) - \mathbf{d}_i^{obs}\right)\right\|_{L_2}, \tag{3}$$

$$\Phi_m(\mathbf{m}) = \frac{1}{2}\|\mathbf{Wm}\|_2^2 \tag{4}$$

where $\|\cdot\|_2^2$ represents an L_2-norm, and all quantities written in bold represent vectors. The subscript i refers to the index of multiple models (dataset), $\mathbf{G}(\mathbf{m})$ is the forward functional, $\mathbf{d}^{obs}$ is the observed data vector, and $\mathbf{m}$ is the unknown model vector. $\mathbf{W}_d$ is the data weighting matrix, which ensure the data by giving appropriate weights in the inversion (see Eq. (15) in Pidlisecky et al., 2007). The regularization term $\mathbf{W}$ is chosen as the first- and second-order spatial derivatives (Zhu and Harris, 2015). A finite-difference approximation of the $\mathbf{W}$ in 3D results in the sparse matrix

$$\mathbf{W} = a_x\mathbf{G_x} + a_y\mathbf{G_y} + a_z\mathbf{G_z} + a_{lap}\mathbf{L} \tag{5}$$

where a_x,a_y and a_z are relatively weights applied to x, y, and z spatial components of the discrete gradient ($\mathbf{G_x}$,$\mathbf{G_y}$,$\mathbf{G_z}$) (Pidlisecky et al., 2007), $\mathbf{L}$ is the discretized Laplacian matrix (Aster et al., 2005), and a_{lap} is the weighting value.

For our problem, the cross-gradient function is chosen as the constraint functional $\psi_{cc} = \psi_{cg}(\mathbf{m}_1,\mathbf{m}_2)$. The constraint functional is defined as $\psi_{cg}(\mathbf{m}_1,\mathbf{m}_2) = \|t\|_2^2$, where the cross-gradient function t is defined in Gallardo and Meju (2003):

$$t(x,y,z) = \nabla\mathbf{m}_1(x,y,z) \times \nabla\mathbf{m}_2(x,y,z), \tag{6}$$

where ∇ is the gradient in the x, y and z directions. The structural similarity requires $\boldsymbol{t} = 0$, which means that any spatial changes occurring in both $\mathbf{m}_1$ and $\mathbf{m}_2$ must point in the same or opposite direction, or no spatial changes in one of $\mathbf{m}_1$ and $\mathbf{m}_2$ (Gallardo and Meju, 2004). The derivatives of the cross-gradient term with respect to the model parameters are given in 2D (Gallardo and Meju, 2004) and 3D (Tryggvason and Linde, 2006). The Jacobian matrix $\mathbf{J}_{xg}$is then obtained. Each row of Jacobian matrix has six nonzero elements of $2N_m$ (N_m is the model size) (cf. Gallardo and Meju, 2004, Eq. (9)).

In our synthetic and field examples, we carefully choose λ through several tests to balance model misfit and data misfit in the independent inversion. When λ is obtained, we use this value for the iterative joint inversion. We determine the β value by the experienced rule given by Hu et al. (2009)

$$\beta = 10^L|\Phi_m|^2/\left[N\left(|\psi_{cc}|^2 + \delta^2\right)\right], \tag{7}$$

where $N = N_xN_yN_z$ and δ is a small value. L usually ranges $0<L<5$ and depends on which model is superior, i.e., the superior model has relatively small weights. N_x, N_y and N_z are the number of discretized grid points in the x, y and z directions.

Fig. 1 shows the flowchart of our iterative procedure. The procedure begins with two input datasets and their corresponding initial models $\mathbf{m_0} = (\mathbf{m}_1,\mathbf{m}_2)$, which are usually homogenous in our tomography algorithm. In the first iterative, we run two independent inversions (box 'A' and 'B') for $\mathbf{m}_1^1$ and $\mathbf{m}_2^1$. The superscript denotes the iteration number. When we obtained updated models $\mathbf{m}_1^1$ and $\mathbf{m}_2^1$ from flows 'A' and 'B'

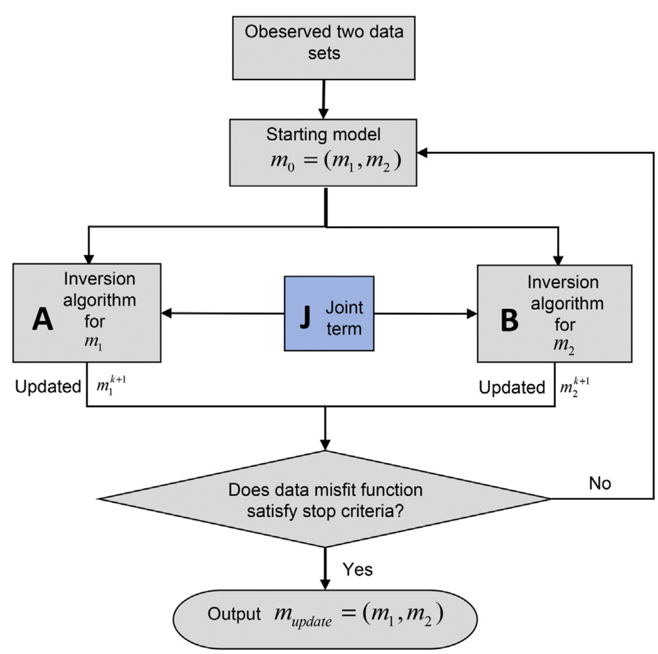

Fig. 1. Flowchart of iterative joint inversion scheme. The boxes 'A' and 'B' represent the independent inversions. The box 'J' represents the joint constraint term between 'A' and 'B'.