S1–20

# Data–Space Cross–Gradient Joint Inversion of Multiple Geophysical Data

*Pak Yong Chol* *, *Kim Kang Sop*

Faculty of Resources Exploration, Kim Chaek University of Technology, Pyongyang, DPRK
*Corresponding author: Email: pyc80525@star–co. net. kp

This paper proposed an approach to implement the cross–gradient joint inversion of multiple geophysical data in the data–space. Presently, most of the existing cross–gradient joint inversion methods use the Gauss–Newton (GN) method, Quasi–Newton (QN) method and conjugate gradient (CG) type method for their optimization algorithm. The main advantages of GN–type are its stability and robustness and limited memory optimization schemes such as QN and CG needn't directly construct the full Jacobian matrix and the large and dense coefficient matrix of the system of equations. Meanwhile, GN–type inversions require fewer iterations to converge to the solution than limited memory methods.

We treat a data–space method based on GN–type joint inversion, aiming at less iteration and less memory consumption. We explain how to formulate the data–space cross–gradient joint inversion and how it effectively reduces the memory requirement.

Actually, with the data–space approach, the part of the parameter space that has no effect on the data is eliminated and the system of normal equations in the model–space is replaced by a system in the data–space. In general cases, the number of data parameters is less than that of model parameters by a large factor, and the memory required to store the system of equations is much smaller in the data–space method than in the model–space method. Thus the data–space method has both advantages of less memory and iterations.

In this paper, we generalize GN–type multiple cross–gradient joint inversion by introducing an integrated model parameter and an integrated data parameter and solve the inverse problem in the data–space. The well–known matrix identity is implemented for the derivation of the data–space formulae from the traditional model–space formulae. In solving the Lagrange multiplier, we use iterative solver such as QMR to avoid the calculation of the large inverse matrix. Instead of constructing the model covariance matrix directly, the products of it with any model vector, which are required in the inversion scheme, are computed by solving a diffusion equation. The diffusion equation has to be repeatedly solved with the QMR, but storing a temporary matrix of small dimension enable to largely improve the computational efficiency. For the special case, when each of the datasets is sensitive to only one set of model parameters, we can calculate the model updates by datasets.

The data–space method, as GN–type method, has advantages of stability, robustness and less iteration than other optimization schemes (QN or CG). And the size of normal equation equals to the number of data parameters, so it can save much memory over the model–space method.

In order to demonstrate the proposed method, we use the magnetotelluric (MT), gravity and magnetic data observed in a study area. The profile trends NW–SE and is about 14km long, MT impedances for 21 frequencies, that ranges from 1.41 to 10 400Hz at 14 stations, were estimated and Bouguer and total magnetic intensity (TMI) data were extracted with 200 m spacing along the profile to obtain the two sets of 73 potential field data for inversion.

We first solve the separate inversion and the three solutions obtained represent the observed data with rms misfit values of 9.99, 1.09 and 0.91. In the results of the separate inversion, we can hardly find any structural similarity between different physical properties. The joint inversion in the model–space and the data–space yields similar rms misfit values of 10.02, 1.13, 1.18 and 10.01, 1.12, 1.20, respectively, and both inversions converge to solutions at the $8^{th}$ iteration. The resistivity, density, and susceptibility models of results are structurally coupled very well, and results of the model–space method and the data–space method are not much different. But because the number of model parameters is 7 250 and numbers of data parameters are 588 for MT, 73 for gravity and magnetic method, the memory requirements are about 1 325Mbyte and 81Mbyte for model–space and data–space methods in the inversion. The larger the model size, the more the difference of memory consumption.

We firstly applied the data–space method to the geophysical joint inversion and evaluate its effectiveness. In the cross–gradient joint inversion, the data–space method can yield nearly same results in about equal time with the model–space method and requires much less memory, so can be applied large–scale problems including 3D joint inversions. It also can be applied to any sensitivity relationship of geophysical model sets and observation datasets, because it derived from the generalized object function of the joint inversion. The data–space method is expected to be applied to other joint inversion such as the structural–coupled joint inversion using the joint total variation.