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New Advances for a joint 3D inversion of multiple EM methods

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SUMMARY

Electromagnetic (EM) methods are routinely applied to image the subsurface from shallow to regional structures. Individual EM methods differ in their sensitivities towards resistive and conductive structures as well as in their exploration depths. Joint 3D inversion of multiple EM data sets can result in significantly better resolution of subsurface structures than the individual inversions. Proper weighting between different EM data is essential, however. We present a recently developed weighting algorithm to combine magnetotelluric (MT), controlled source EM (CSEM) and DC-geoelectric (DC) data. It is well known that MT data are mostly sensible to regional conductive structures, whereas, CSEM and DC data are more suitable to recover more shallow and resistive structures. Our new scheme is based on weighting individual components of the total data gradient after each model update. Norms of each data residual are used to assess how much weight individual components of the total data gradient must have to achieve an equal contribution of all data sets in the inverse model. A numerically efficient way to search for appropriate weighting factors could be established by applying a bi-diagonalization procedure to the sensitivity matrix. Thereby, the original inverse problem can be projected onto a smaller dimension in which the search of weighting factors is numerically cheap. We demonstrate the efficiency of the proposed weighting schemes and explore the model domain with synthetic data sets.

Keywords: 3-D forward modelling, Inversion, Joint Inversion.

INTRODUCTION

Electromagnetic (EM) methods differ in their resolution depths from few meters to several 100’s of km. Magnetotelluric (MT) data can resolve conductive structures up to upper mantle depths, controlled source EM (CSEM) and DC-geoelectric (DC) resolve mostly resistive shallow structures. Inverting multiple EM data sets jointly can result in significantly better resolution of subsurface structures than the individual inversions. Because of different resolution capacity and sensitivity patterns of the EM methods, a proper weighting between multiple EM data sets is substantial. Earlier work in this regard based on weighting the individual EM data sets by multiplying the error of each data set with a constant factor. Commer and Newman (2009), for instance, suggested up-weighting the data set which has less data points by multiplying the assigned data errors with a factor obtained from the ration between the numbers of data points. In this scheme, weighting is applied once as the data errors as well as the number of data points remain unchanged in the course of the inversion. A disadvantages of this scheme is the assumption that the data set with less data points must -get more weight, which is not generally valid (as we will demonstrate later). Moreover, applying the weighting only once in the course of a joint inversion, does not allow for a re-weighting if the data misfit of one data set converges to a desired level.

In this study we propose weighting schemes which are mainly based on analysing the data gradients computed after each model update. In gradient based inversion algorithms (e.g. the Non Linear Conjugate Gradient, NLCG) a minimizer of the penalty function is searched along the computed gradient using a line search algorithm (e.g., Egbert and Kelbert, 2012). In case of inverting two EM data sets jointly we observe (by analysing the data gradients computed after each NLCG iteration) that the difference between the norms of the data gradients is typically several orders of magnitude. The difference between the norms of the gradients reflects the resolution capacity and hence the sensitivity of each data set towards changes in model parameters. Without applying a proper weighting, structures required by the data set with a large gradient dominate the inverse model (Fig.1d). By simply up-weighting the smaller gradient and down-weighting the larger gradient an equal distribution of structures required by both data sets can be reached (Fig.1e).

Because of the non–quadratic form of the penalty function, a gradient based inversion algorithm requires a large number of iterations to reach the desired data misfit. In the Gauss-Newton approach in which the penalty function is quadratic, only few iterations are required to obtain the minimum of the function. Solving the normal equations, which is required by the Gauss-Newton approach, however, is costly in terms of memory storage and a long run times. Even the Gauss-Newton variant in the data space (Siripunvaraporn and

Egbert, 2000) has large memory requirements to store the full sensitivity matrix. One possible way to overcome memory problems is using the conjugate gradient (CG) method as a solver of the normal equations. In this case, instead of saving the full sensitivity matrix only matrix-vector multiplications are required to find a solution for the normal equations (e.g. Mackie and Madden, 1993). A disadvantage of the CG method is encountered when searching for an optimum value for the regularization parameter. In practice, for each value of the regularization parameter tested, the full set of normal equations has to be solved. Based on the Lanczos bi-diagonalization algorithms of Paige and Saunders (1982), Egbert (2012) showed that by saving the orthonormal data and model search direction vectors computed in each CG iteration, the original dimension of the normal equation can be projected and stored in much smaller dimensions. For the 2-D inversion of MT data, Egbert (2012) demonstrated that finding an optimum the regularization parameter of an Occam-type inversion in the sub-projected system is computationally very cheap.

In our second approach of 3-D joint inversion of multi-EM data we extended the Hybrid CG-Occam inversion idea of Egbert (2012) to search additionally for an optimal value of weighting parameters. Our proposed weighting algorithm follows basically the same algorithm described in Egbert (2012) up to the point where the model is updated. At that point we split the data gradient used to update the model into components related to each EM data type used in the joint inversion. Similar to the first proposed scheme we up-weight and down-weight the gradient of each data set based on the amplitude of their individual norms.

The proposed weighting schemes are implemented in the framework of ModEM (Egbert and Kelbert, 2012) which allows high flexibility to include any EM method into the structure of the system.

Using synthetic data sets we demonstrate the efficiency of the proposed weighting schemes and the capability of the 3-D joint inversion of EM data in recovering multi scale conductive and resistive structures. Figure 1e shows inversion results of applying our first proposed weighting scheme together with results of inverting MT (b) and CSEM (c) data separately and jointly, but un-weighted (d).

REFERENCES

Commer M. and Newman G.A, 2009, Three-dimensional controlled-source electromagnetic and magnetotelluric joint inversion, Geophysical Journal International, 178, 1305-1316.

Egbert, G. D. and A. Kelbert, 2012, Computational Recipes for Electromagnetic Inverse Problems, Geophysical Journal International, 189: 251–267.

Egbert, Gary D., 2012, Hybrid conjugate gradient-Occam algorithms for inversion of multifrequency and multitransmitter EM data, Geophysical Journal International, 190, 255-266.

Mackie R L, Madden T R., 1993, Three-dimensional magnetotelluric inversion using conjugate gradients, Geophysical Journal International, 115, 215-229.

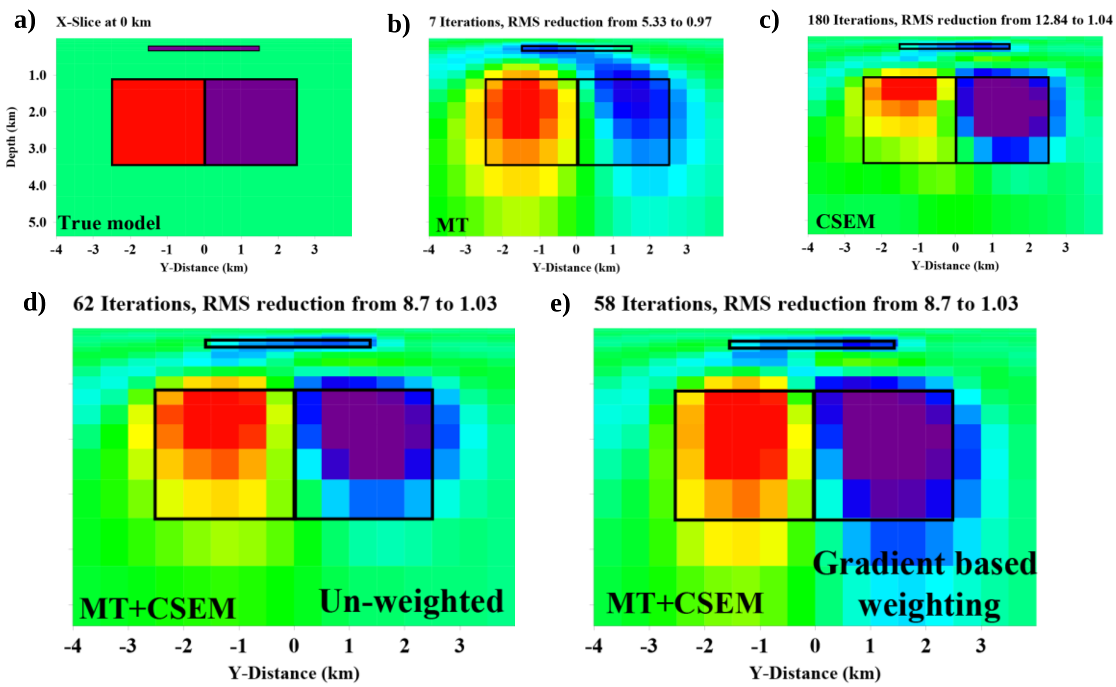

Figure 1: Results obtained from inverting MT and CSEM data separately and jointly. The true 3-D model consists of a shallow and thin resistive block and two deeper conductive and resistive blocks. For the joint inversion results we applied our proposed gradient based weighting scheme.

a) The cross section at x=0 of the original 3D model. b) and c) show 3D inversion results of MT and CSEM data separately. As can be seen in b) and c). the deep conductive block is better resolved by MT while the shallow resistive block is better resolved by CSEM. d) shows the joint inversion result of un-weighted data, which is dominated by structures required by the CSEM data. e) shows 3D joint inversion result after applying our proposed gradient based weighting scheme. In (e) both, resistive and conductive structures are better resolved than with inversions of the individual methods.