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Advanced Modeling and Inversion Tools for Controlled Source EM

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SUMMARY

Modeling and inversion of CSEM data is a challenging problem.

In this work we present a combination of methodologies that allows for the solution of such problem using reduced in a computational efficient way. Our framework is composed from three main parts

1. An adaptive mesh, that is adapted to the sources and receivers, that decreases the size of each linear system to be solved.
2. A multiscale approach that allows us to use large cells far away from the sources and receivers and correctly average or upscale the conductivity.
3. A stochastic programming approach that allows for the reduction of the number of forward modeling at each step of the inverse problem

Introduction

Modeling and inverting electromagnetic data that is generated by many sources and measured by equivalently amount of receivers, in multiple frequencies, in a highly heterogeneous environment that contain nontrivial bathymetry is an important challenge for controlled source electromagnetic experiments. The difficulty stems from three main components. First, the simulation area tends to be rather large and discretizing it requires many cells. This leads to very large-scale linear systems for the solution of the forward problem. Second, since the number of sources and receivers is large, the number of forward modeling that is needed, can be very large. Finally, the inverse problem requires the solution of the forward problem many times. This implies that in order to obtain a solution, one requires hundred of thousands or even millions of solutions to the forward problem and this is non-feasible without using massively parallel computing.

In this work we present a combination of methodologies that allows for the solution of such problems using rather modest computational tools. Our framework is composed from three main parts

1. An adaptive mesh, that is adapted to the sources and receivers, that decreases the size of each linear system to be solved.
2. A multiscale approach that allows us to use large cells far away from the sources and receivers and correctly average or upscale the conductivity.
3. A stochastic programming approach that allows for the reduction of the number of forward modeling at each step of the inverse problem.

In the following we expand on each of these components and show that when jointly combined can be used to effectively solve large-scale problems with multiple sources, receivers and frequencies.

Method and/or Theory

Maxwell's equation can be written in terms of the electric field $\mathbf{E}$ and the magnetic flux $\mathbf{B}$ as

$$-\omega \mathbf{B} + \nabla \times \mathbf{E} = \mathbf{0},$$

$$\nabla \times \mu^{-1} \mathbf{B} - \hat{\sigma} \mathbf{E} = \mathbf{j}_s$$

where $\mathbf{j}_s$ is the source, ω is the frequency and σ is the conductivity. To deal with this problem we discretize it using either an OcTree mesh or a tetrahedral mesh. Both meshes allow us to use small cells where the fields change quickly, in the vicinity of the sources (and the receivers for the adjoint problem) and in the presence of bathymetry or large conductivity contrast. The use of adaptive mesh immediately reduces the number of cells to be used for the forward problem as we can avoid the fine discretization of areas that are far from the sources and receivers. Nonetheless, the presence of non-trivial bathymetry requires small cells. However, using multiscale techniques it is possible to coarsen areas that contain highly variable bathymetry. Multiscale methods are special upscaling techniques that are based on local solution of Maxwell's equations (see Haber & Ruthotto 2014). Using multiscale techniques we are able to further reduce each mesh to have only a few thousands of cells. We then use either finite volume or finite elements for the discretization of Maxwell's equations on our mesh, allowing the use of direct matrix factorization for the solution of each forward problems quickly.

Next, we attempt to solve the inverse problem that can be formulated as a minimization problem

$$\phi(\mathbf{m}) = \mathbf{F}(\mathbf{m}) + \alpha \mathbf{R}(\mathbf{m})$$

where $\mathbf{F}$ is the misfit, $\mathbf{R}$ is the regularization and α is a regularization parameter. For problems with many sources the misfit admits the following structure

$$\mathbf{F}(\mathbf{m}) = \frac{1}{2} \sum_{k=1}^{n_s} (\mathbf{d}_k(\mathbf{m}) - \mathbf{d}_k^{obs})^\top \mathbf{W}_k^\top \mathbf{W}_k (\mathbf{d}_k(\mathbf{m}) - \mathbf{d}_k^{obs})$$

where the summation is on the different sources. Recent efficient minimization algorithms are based on stochastic programming (see for example Aravkin et-al and reference within) use very few sources at each optimization step to solve the problem, reducing the cost of each iteration significantly.

Example

In this section we briefly present an example that demonstrates the reduction in computational time that is obtained by using our methodology. We consider the detection of a resistive reservoir inside a conductive earth in the presence of non-trivial bathymetry. The bathymetry and model as well as the mesh for the inverse problem is presented in Figure 1.

Figure 1 Our conductivity model has the non-trivial bathymetry (left). The conductivity (middle) contains a resistor in a randomly conductive media. The area of interest is discretized by a mesh on the right.

We assume 1024 sources and 6 frequencies and use our methodology in order to recover the conductivity. The recovery takes about 6 hours on a 12 processor desktop with 64Gb or RAM. The recovery and the convergence is presented in Figure 2.

Figure 2 Slices of the recovered conductivity (left and middle) that show the recovery of the reservoir and the convergence history (right).

Conclusions

We have presented a framework that allows the inversion of massive amount of data for multiple sources, receivers and frequencies in the presence of nontrivial bathymetry. We have tested our methodology on a synthetic model that represents typical hydrocarbon recovery and found it to yield reasonably accurate results in a short computational time

References

Aravkin, A., Friedlander, M.P., and van Leeuwen, T. [2012] Robust inversion via semistochastic dimensionality reduction. *IEEE Conf. Acoustics, Speech, and Signal Proc.*

Haber, E. and Ruthotto, L. Multiscale methods for Maxwell's equations in low frequencies, Submitted to GJI