Using deep learning for model error estimation in 3D probabilistic inversion of controlled-source electromagnetic data

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Summary

We propose a 3D Markov Chain Monte Carlo (MCMC) inversion of controlled-source electromagnetic (CSEM) data to image oil reservoirs. Simulation of the CSEM response with complex 3D geological structures becomes challenging when a large number of forward computations are required, which is the case when performing a probabilistic inversion. We use a parallel structure and an efficient nonconforming finite element algorithm to calculate the electromagnetic response by discretizing the diffusive frequency-domain Maxwell's equations. We compute the differences between solutions calculated with the same forward solver but with two different discretization sizes, and we use deep learning techniques to determine a low-dimensional probabilistic representation of this model discrepancies. We use this representation as prior information in the probabilistic inversion, which is then set to characterize not only the subsurface model parameters, but also the model errors caused by the use of the computationally-cheap coarse discretization.

Based on an array of receivers, we construct multichannel images of the field discrepancy between models for different frequencies and field components. We train a spacial generative adversarial network (SGAN) with those images, demonstrating that the network is able to capture the distribution function of the model error. The trained generator is added to the MCMC inversion algorithm. Then, at each step of the MCMC computation the forward response is corrected with a model error realization of the network.

We propose a synthetic marine CSEM experiment to test the MCMC recovery of model parameters and model error. We evaluate the feasibility of the method and emphasize the advantages of estimating modeling error and the use of a computationally-cheap forward model. This approach provides a complete probability distribution of the model parameters retrieved by the inverse problem. Assessing model uncertainty contributes to a more comprehensive interpretation of the geophysical measurements.

Keywords: Probability distributions, Neural networks, Controlled source electromagnetics