# Probabilistic inversion of magnetotelluric data and uncertainty quantification

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The magnetotelluric (MT) method is a well-established tool for imaging the resistivity structures from the surface down to hundreds of kilometers, which provides important constraints on Earth’ s internal properties and geodynamic process. The inversion is routinely performed to quantitatively extract information about electrical conductivity distributions of the subsurface from measured MT data. However, the MT inversion is characterized by inherent nonuniqueness due to noisy observations and incomplete data coverage, which means that there are many different equivalent models that explain the observed data adequately well, thus resulting in significant uncertainty in the derived model parameters. Therefore, a quantitative uncertainty analysis is essentially indispensable for reliable interpretation of MT data. Gradient-based deterministic inversion approaches are commonly used and computationally efficient, but they usually produce only one single preferred model that fits the observed data under predefined model regularization without sufficient information to accurately quantify the model uncertainty.

In this study, we have developed a Bayesian inversion framework for probabilistic inversion of 2D MT data. By postulating the inverse problem into a sampling-based Bayesian inference framework, we can rigorously estimate model uncertainty associated with the inverted model parameters using a large ensemble of models sampled from the posterior distribution of model parameters. Here, we present two Bayesian algorithms: the transdimensional Markov chain Monte Carlo (MCMC) and Hamiltonian Monte Carlo (HMC) methods for inverting MT data. The transdimensional MCMC uses a flexible parameterization where the electrical resistivity model is partitioned by a variable number of Voronoi cells, thus the level of model complexity will be automatically determined and adapted to the spatial resolution of the observed data during the inversion. However, it surfers from the slow convergence of the Markov chains, especially in high dimensional model space. In contrast, the HMC method can efficiently explore the model space and produce samples with much higher acceptance probabilities than MCMC by making use of gradient information of the posterior distribution, but the model parameterization is kept fixed during the HMC inversion. We demonstrate and compare the performance of these two algorithms with synthetic and field MT datasets, and discuss their main benefits and drawbacks. In addition, we explore some useful techniques such as parallel tempering and surrogate modeling to accelerate the convergence of the Markov chains and alleviate the computational burden, making the probabilistic inversions more tractable for practical MT applications.

Keywords: Magnetotelluric, Probabilistic inversion, Uncertainty quantification, Transdimensional MCMC, Hamiltonian Monte Carlo