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Imaging lithospheric interfaces and 3D structures using receiver functions, gravity, and tomography in a common inversion scheme

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ABSTRACT

Joint inversions are now commonly used in the earth sciences. They have been developed to better understand the structure of the earth, since they provide more constraints on the inverted parameters. We propose a new process to simultaneously invert several data sets in order to better image 3D crustal and upper mantle structures. Our inversion uses three kinds of data that present good complementarity: (1) P-wave receiver functions to provide Moho depth variations, (2) teleseismic delay times of P-waves to retrieve velocity anomalies in the crust and the upper mantle, and (3) gravity anomalies to image density variations at the lithospheric scale. We use a stochastic scheme, where receiver functions are first inverted. The interpolated resulting Moho depths are incorporated as a priori information into the joint inversion of teleseismic delay times and gravity anomalies process. Moreover, velocity and density can be linked by empirical relationships, which justifies the joint inversion of those parameters. In our stochastic approach, we perform a model space search for Moho variations, P-velocity, and density structure to find an acceptable fit to the three data sets. In order to preferentially sample the good data fit regions, we chose the neighborhood algorithm of Sambridge to optimistically survey the model space. We model the delay times with 3D raytracing using evenly spaced velocity–density nodes. We present here the first results given by this method on synthetic tests.

1. Introduction

Cooperative inversions of geophysical data have been introduced by Lines et al. (1988). The aim of this concept is to obtain a geophysical model consistent with multiple datasets. Two different philosophies have been defined depending on the inversion procedure: sequential or joint inversion. In the sequential approach, the inversion for a particular data set provides the input or initial model estimate for the inversion of a second data set; joint inversion treats all the datasets simultaneously. However, in this second process, the datasets should be linked with a relationship.

Whichever approach is used, the user faces the difficulty of solving the inverse problem and thus the choice of an adapted algorithm. Classically, during the past decades, most geophysical inverse problems were solved by inverting matrices using methods such as weighted least-squares analysis (e.g., Menke, 1984; Aki et al., 1977). Joint inversions of geophysical data in general were developed following this procedure (e.g., Lees and VanDecar, 1991a; Maceira and Ammon, 2009; Julia et al., 2000; Parsons et al., 2001; Tikhotsky and Achauer, 2008). However, the use of stochastic methods have become increasingly successful due to the extreme growth of computing power, the gathering of computing resources (clusters and national and international grids), and the development of probabilistic methodology (Tarantola and Valette, 1982). These approaches (Monte Carlo, neighborhood algorithm, etc.) randomly investigate the model space to propose a set of models minimizing the data misfit (e.g., Moorkamp et al., 2010; Bosch et al., 2006; Kozlovskaya et al., 2007). One advantage is that they keep track of all tested models, and the user can then choose the one(s) best fitting his or her a priori prerequisite. Moreover, as only direct calculations are needed, we avoid mathematical approximations, global damping procedures, and the often subjective process of finding an optimal regularization value (e.g., Bodin et al., 2009). In addition, we overcome extensive matrix management.

Linearized inversions are greatly dependent on the initial model. Consequently, their results can be irrelevant when only little a priori information is added. (Chang et al., 2004). The use of a stochastic algorithm can therefore be appropriate. Moreover, solving highly nonlinear problems by direct calculations rather

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than matrix inversion proves to be more relevant (Zeyen and Achauer, 1997). We thus propose to combine a stochastic algorithm with a joint inversion of seismological and gravimetric data in order to image the perturbing structures at a lithospheric scale.

Among all the stochastic methods, we use the neighborhood algorithm (NA), already tested and validated for several geophysical applications (among others: receiver functions (Sambridge, 1999a), seismic events location (Sambridge and Kennett, 2001), waveform inversion for surface waves (Yoshizawa and Kennett, 2002)). This method is performed on one hand on gravity and teleseismic delay times for their good complementarity (e.g., Nafe and Drake, 1957; Birch, 1961); on the other hand on receiver function to solve for major interface geometry. The introduction of the latter is essential to distinguish between real velocity–density anomalies and interface fluctuations.

We investigate this new approach through different synthetic tests. Also, we develop a misfit function that takes into account the dissimilarities between the two data set populations. By using the receiver function results as *a priori* information into the inversion scheme, the user is then able to weight the data sets to retrieve both interfaces and 3D velocity–density structures within the lithosphere and asthenosphere.

2. Consistency and complementarity

Joint inversions result from the necessity to improve geophysical data inversion with additional constraints. Thus, they are meaningful only if there is a complementarity between independent data sets either by physical laws (e.g., Bosch and McGaughey, 2001, for joint inversions of gravity and magnetic data) or by common geometry or parameters (e.g., Julia et al., 2002, or Gallardo and Meju, 2007 for joint inversions of receiver functions and surface waves). In our case, we jointly invert gravity data and teleseismic P-wave delay times in order to retrieve the velocity–density structure, taking advantage of empirical relationships between those parameters (Birch, 1961). Also, we include Moho depth variations obtained from the inversion of the P-wave receiver function as *a priori* information in the joint inversion process.

Potential field interpretation suffers from the well-known nonunique determination of the source parameters from its field data. This is not only because of an insufficient knowledge of the field with respect to the number of unknown source parameters or to errors of theoretical and experimental nature, but also coming from inherent nonuniqueness (Blakely, 1995; Fedi and Rappola, 1999).

One benefit of jointly inverting gravity and seismic tomography is the complementarity between their best-resolution areas. Indeed, the resolution of regional teleseismic tomography depends on ray coverage and increases with depth, with a gap near the surface (0–50 km). However, at these depths, gravity inversions using the terrestrial Bouguer anomaly reach their best-resolution rate.

A second advantage of considering velocity and density is the existence of simple empirical relations (Nafe and Drake, 1957; Birch, 1961) linking those two parameters. Density and velocity are usually inverted cooperatively (e.g., Vernant et al., 2002, or Lees and VanDecar, 1991b for sequential inversion and joint inversion, respectively) using a constant linear relationship between density and velocity (e.g. Birch, 1961). The velocity–density joint inversion of Tiberi et al. (2003) used the approach suggested by Zeyen and Achauer (1997) and Jordan and Achauer (1999) to treat the B factor linking velocity and density variations as a parameter allowed to vary around a given value. However, this process leads to a highly nonlinear problem that is hardly resolved by standard linear inversion of matrix (Tiberi et al., 2003; Basuyau et al., 2010). In our inversion scheme, we link velocity V_P and density ρ using Birch's law (1961),

$$V_P = B\rho + A,$$

where A and B are constant parameters for each layer whose values are chosen by the user. The two parameters can therefore take different values with depth to better depict the correlation between velocity and density (Christensen and Mooney, 1995). In our method, B and A are constant parameters because considering them as varying parameters lead to a too highly nonlinear problem (Zeyen and Achauer, 1997).

Many of the regional tomographic methods (e.g., the ACH method from Aki et al., 1977) set the initial model up as successive horizontal layers so that Moho depth variations appear as velocity anomalies within the horizontal layers. However, in many geodynamical contexts, such as passive margins or convergence zones, the approximation of nonexistent Moho depth variations is not justified and can lead misinterpretation. The method we present here proposes to consider Moho depth variations obtained by the inversion of receiver functions in a joint inversion scheme for both tomographic and gravity data. In addition, we used an algorithm that gives absolute velocity and density instead of anomalies as usually obtained in regional teleseismic tomography (e.g., ACH methods, Lévêque and Masson, 1999).

3. Inversion procedure

The structural organization of the inversion is illustrated by the flowchart in Fig. 1. The code is organized in two independent parts: the first part is dedicated to the inversion of receiver function and in the second part density and velocity are inverted. As we use the same stochastic algorithm for both parts, we dedicated the first paragraph of this section to its understanding.

3.1. Neighborhood algorithm

We use a stochastic method called the neighborhood algorithm (NA) (Sambridge, 1999a,1999b) that makes use of geometrical constructs known as Voronoi cells to drive the search in parameter space. The cells are used to construct an approximate misfit surface at each iteration, and successive iterations concentrate sampling in the regions of parameter space that have low data misfit.

Unlike previous methods (e.g., linearized inversions), the objective is to generate a set of models with an acceptable data fit rather then to seek a single optimal model. The entire ensemble can be used to extract robust information about the model parameters, such as resolution and tradeoffs. This is performed within a Bayesian framework and is discussed in more detail in Sambridge (1999b). Even though global optimization is not the primary objective of the NA, it has been shown to work well in this respect for both receiver function inversion (Sambridge, 1999a) and seismic event location (Sambridge and Kennett, 2001). The behavior of the search algorithm is controlled by two parameters, n_s and n_r (with $n_s \geq n_r$), where n_s is the number of models tested at each iteration and n_r is the number of Voronoi cells resampled at each iteration. The NA can be summarized by the following:

- First, n_s models are randomly generated, and a misfit value is calculated for each model.
- Next, the n_r models with the lowest misfit are determined, and a random walk is performed inside their Voronoi cells in order to generate a new set of n_s models.