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Geological Consistency From Inversions of Geophysical Data

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Summary

A subsurface volume that can be reliably interpreted in terms of geologically relevant parameters is a desirable outcome from depth inversion workflows. Geophysical data are often inaccurate and incomplete, the inverse problem is commonly non-unique, and constraints are usually required to recover useful output models.

We introduce a novel application of the established cross-gradient operator to incorporate surface or sub-surface geological and other attribute measurements in a data-driven workflow, delivering a model consistent with all the available information.

Two field data examples are presented: in the first we constrain an airborne electromagnetic inversion with surface geology observations (dip and strike); secondly we employ a seismic volume to constrain a marine controlled-source electromagnetic inversion, where a structure tensor operator is used to derive the directional information.

Introduction

A subsurface volume that can be reliably interpreted in terms of geologically relevant attributes is a desirable objective for products from depth inversion workflows. Geophysical data are inherently inaccurate (noise, aliasing, etc.) and the inverse problem is commonly non-unique, so an implementation of some type of constraint is required to recover reasonable output models.

We illustrate a cross-gradient inversion where surface geological information is included in the input data set, building on the work described by Scholl et al. (2015 and 2016). The basic application covers the usual structural similarity objective, comparing the gradient fields of property volumes derived from different geophysical domains. A distinct advantage comes when gradient control from surface or subsurface geology, or any ancillary property set, is included during single or joint domain inversions of geophysical data.

Methodology

Gallardo and Meju (2003) introduced the cross-gradient concept for the joint inversion of different geophysical methods; 2D DC resistivity and seismic in that specific case. The idea is to quantify structural similarity between two property distributions, rather than inter-property correlation, by looking at the norm of the cross-product of their gradients. This norm is zero if the directions of change in the two models are aligned. It is irrelevant if the values of the model parameters increase or decrease in that direction. Likewise, the strength of the change does not matter. We add the cross-gradient term as an additional regularization term to the inversion cost function:

$$\Phi(\mathbf{m}) = \left\|\left(\mathbf{d} - \mathbf{f}(\mathbf{m})\right)\right\|^2 + \beta \int_V \|\boldsymbol{\nabla}\mathbf{m}\|^2 \, dV + \gamma \int_V \|\boldsymbol{\nabla}\mathbf{m}_\mathrm{A} \times \boldsymbol{\nabla}\mathbf{m}_\mathrm{B}\|^2 \, dV$$

The vectors $\mathbf{m}_\mathrm{A}$ and $\mathbf{m}_\mathrm{B}$ contain two different properties sampled on the same model grid. For a simultaneous joint inversion of two geophysical datasets (e.g. the 3D joint inversion of airborne EM and gravity gradiometry in Scholl et al., 2016) $\mathbf{m}_\mathrm{A}$ and $\mathbf{m}_\mathrm{B}$ are both part of the total model vector $\mathbf{m}$; i.e. $\mathbf{m}_\mathrm{A}$ contains resistivities while $\mathbf{m}_\mathrm{B}$ contains the densities, and $\mathbf{m}$ is composed by concatenating them. The additional regularization term comes with its own trade-off parameter γ. Using the cross-gradient part as sole regularization does not stabilize the inverse process adequately, so additional regularization, e.g. in form of the smoothness term, is necessary. We found it useful to keep γ constant, while adjusting β in order to reach the desired misfit.

Instead of comparing the model gradients of two different property volumes inverted simultaneously, it is possible to introduce *a priori* gradients derived from an auxiliary model or data set. In this case $\mathbf{m}_\mathrm{A}$ is identical to the inverted model vector $\mathbf{m}$, while $\mathbf{m}_\mathrm{B}$ is the auxiliary a priori model that remains unaltered during the inversion. Since only the direction of change matters, arbitrary numerical values can be used to create an auxiliary model resembling geological structures. Alternatively, gradients can be defined directly without setting up a model containing nominal values, so instead of creating an auxiliary model $\mathbf{m}_\mathrm{B}$, the gradients $\boldsymbol{\nabla}\mathbf{m}_\mathrm{B}$ are used as inversion input.

The equation above assumes that all model vectors contain dimensionless quantities. The overall magnitude of $\mathbf{m}_\mathrm{A}$ or $\mathbf{m}_\mathrm{B}$ is not relevant for the cross-gradient regularization, as it will only affect the strength of the regularization, which is adjusted by the trade-off parameter γ. It is possible, however, to scale the a priori gradients based on how reliable the a priori information is in a certain part of the model relative to other parts. For example, in the case illustrated below where surface dips are used to regularize the inversion, the dip-derived gradients are scaled down with depth to reflect that while the dips are well understood at surface they are less so at depth.

Steering with surface geology

Time domain AEM data (Helitem®) were surveyed by CGG in the Alberta foothills area, as part of a near-surface characterization program. The stand-alone (i.e. without cross-gradient) 2D and 3D smooth model inversions capture the main geological units, but the shapes of the anomalies fade out quickly and dips are not very obvious.

Ground measurements of dip and strike are available from the published 1:50000 geology map of Langenberg and LeDrew (2001, shown in Figure 1a here). The accompanying interpreted cross-sections, albeit adjacent to the AEM survey area, illustrate the compressive structural style; outcropping steep thrusts cutting the related fold structures. The actual ground dip measurements were projected into data-poor areas along the mapped geological contacts (Figure 1a). The surface dip data were interpolated component-wise between the ground dip measurements with a minimum curvature spline in tension (Figure 1b). Gradient values were then mapped to the 3D reference model starting from the first earth block downwards. While the dips are well defined at surface, they will change with depth, so in order to fade out the cross-gradient regularization accordingly, the gradients are increasingly smoothed downwards.

When compared to the blind inversion results (Figure 2a) both close to the surface and below, the steered inversion (Figure 2b and 2c) provides a more realistic structural model. In similar workflows, the code facilitates surface geology constraint of a range of single or multiple geophysical domain inversions, including for instance potential fields and seismic.

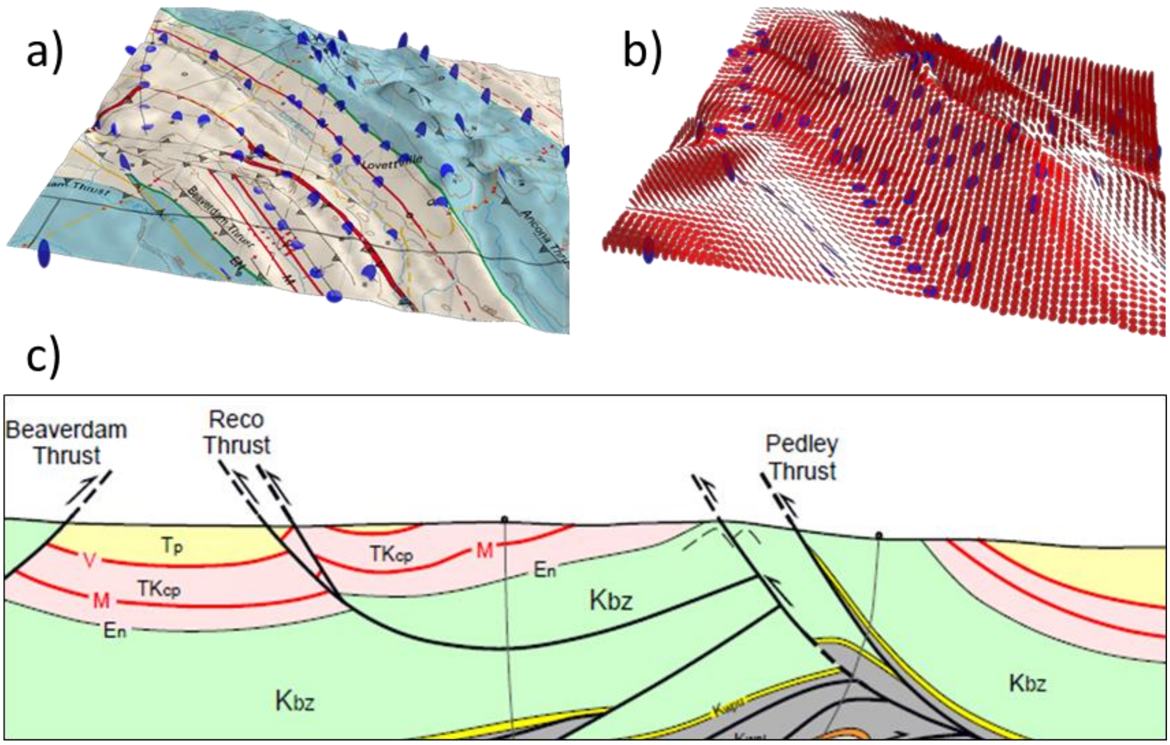

Figure 1: *Geology map (a) extracted from Langenberg and LeDrew (2001) and their SW-NE cross-section (c) through the northwest of the area shown here. On the map - the oriented blue ellipses are the strike and dip points as published on the geology map; red ellipses on the right (b) are interpolations of the input vectorial dip data onto a regular grid.*

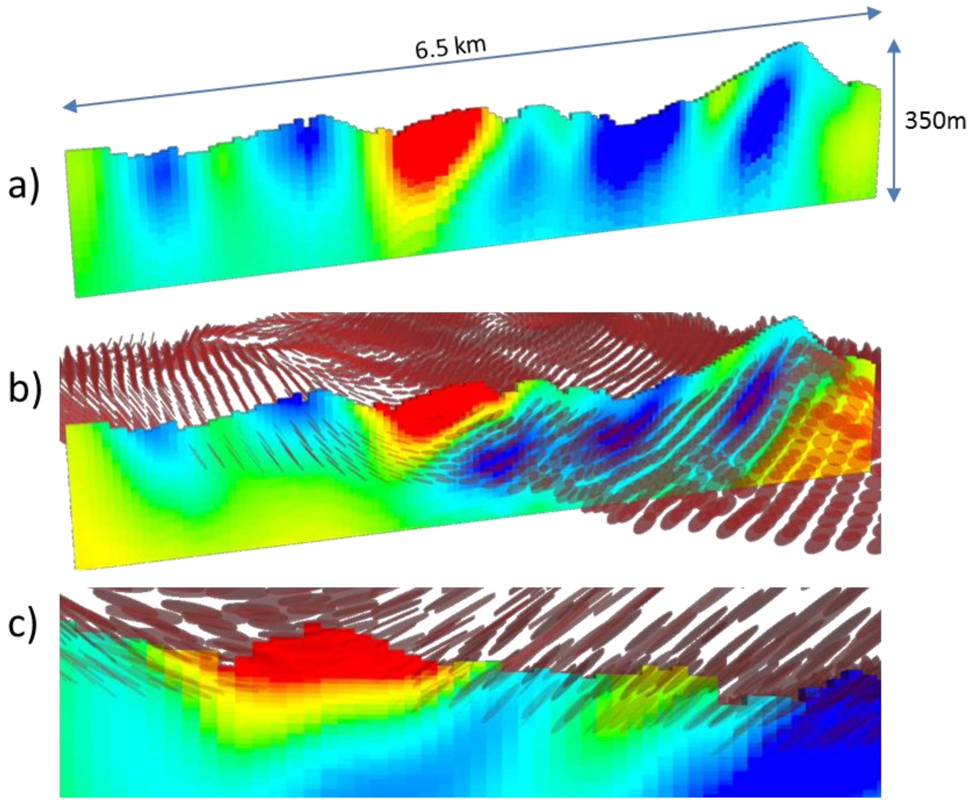

Figure 2: *Slice from 3D inversion of AEM survey data. Unconstrained inversion (a), surface-geology steered inversion (b). Close up on a different slice in the volume (c). Red discs are co-rendered with resistivity to show the effect of the directional constraint on the orientation of the recovered structures. The consistency with the surface measurements is ensured through a high weight in the cross-gradient term in the shallow cells, faded to zero at increasing depth.*

Steering with a seismic image

In this offshore exploration application, the model steering uses depth migrated seismic to constrain a controlled-source EM inversion. The main issue when integrating seismic and non-seismic data is the large difference in resolution. Seismic images can be sampled at more than one order of magnitude higher rates than the meshes used for EM modelling. In order to bring the directional information from the seismic data to a resolution appropriate for EM, we employ the structure tensor (Zhou et al., 2014). This operator is based on an eigenvalue decomposition of averaged gradients within a volume of interest, resulting in a vector field which captures the directions with the most significant variations.

For each cell of the EM inversion mesh, gradients from the seismic image are summed to construct the structure tensor matrix. Shown here is the 2D formulation, which can be easily generalized to 3D:

$$S_1 = \begin{bmatrix} \sum I_x^2 & \sum I_x I_z \\ \sum I_x I_z & \sum I_z^2 \end{bmatrix}$$

The eigenvectors of this matrix represent the directions of the main variation, whereas the eigenvalues represent the strength of the gradient. We incorporate this information in the auxiliary model, which is used for steering the EM inversion by means of cross-gradients. The example in Figure 3 is an application of this technique to marine CSEM data in the Norwegian Sea, whose inversion has been steered based on a seismic image. The focusing of the resistive structures is enhanced and the consistency with the seismic data is improved.

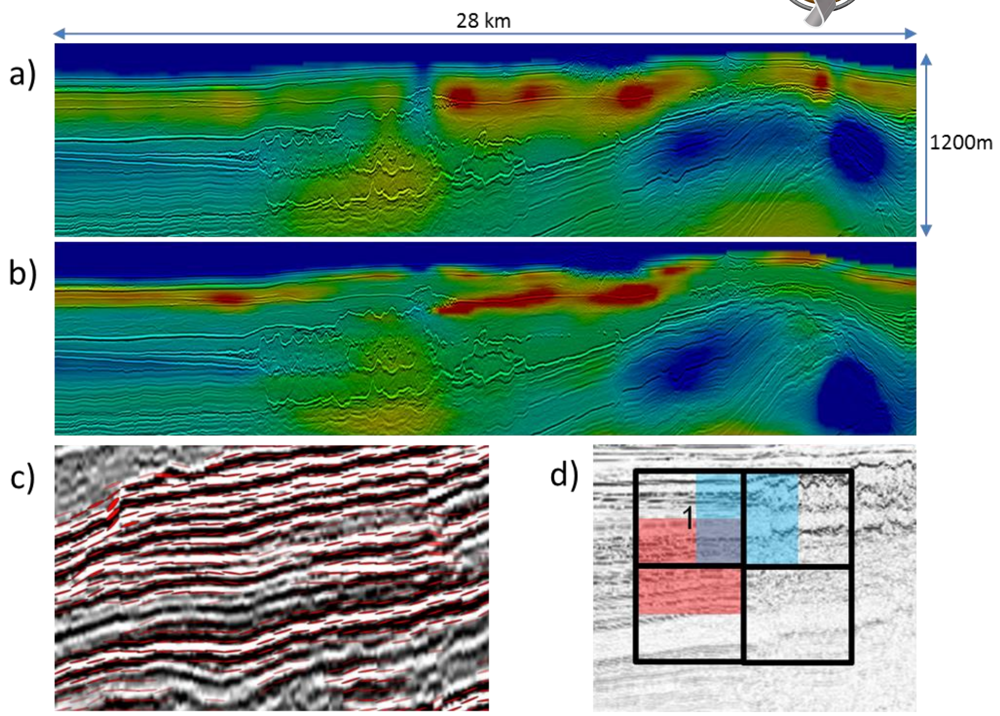

Figure 3: *Seismic image-guided inversion of marine CSEM data. Unconstrained inversion (a), image-guided inversion (b), detail of gradients derived from seismic image (c). Gradients across EM cell boundaries (d) are estimated with a structure tensor operator, in order to bring directional information from high resolution seismic data to a scale appropriate for EM modelling.*

Conclusions

We have implemented the quantitative use of surface or sub-surface geological data during 2D and 3D inversion modelling, providing a result that is consistent with all available data, and hence of increasing plausibility. This is accomplished through steering the inversion using cross-gradient regularization, where the reference gradient model is derived directly from geology. The methodology is generic, and therefore expandable to derive a controlling gradient field from the range of sub-surface attribute data available in exploration, development and production projects.

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