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Integration of remote sensing and ground magnetic data for delineating copper mineralization zones: A Case Study from the Rah-Chaman area, Khorasan Razavi Province, Iran

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Extended Abstract

Summary

Potential field methods, specifically gravity and magnetic methods are the most fundamental geophysical techniques in mineral exploration. The interpretation of the potential field data heavily relies on the inversion or inverse modeling of the data. The inversion of potential field data to estimate subsurface model parameters is a numerically challenging and inherently non-unique problem. An infinite number of models can adequately satisfy the observed data. A crucial approach to mitigate this non-uniqueness is incorporating geological constraints relevant to the survey area. While individual inversions of geophysical datasets often provide satisfactory reconstructions of subsurface anomaly locations, integrating information from multiple geophysical methods is essential for achieving a better recovery and subsequently a more robust interpretation of subsurface structures. In many practical scenarios, single-method geophysical surveys fail to provide unambiguous interpretations. Thus, the combination of geophysical methods is imperative. Joint inversion, whether for identical or different physical parameters, is an effective technique to achieve enhanced resolution. Consequently, a comprehensive geophysical interpretation based on joint inversion has gained widespread application in recent years. This paper investigates a three-dimensional (3D) joint inversion of gravity and magnetic data by utilizing a cross-gradient function to enforce structural similarity. The performance of the joint inversion algorithm is first validated using synthetic model data, and then, the algorithm is applied to real field data to demonstrate its practical efficiency.

Introduction

The most common approach to joint inversion based on structural similarity is the use of the cross-gradient constraint. This methodology was originally developed for the joint inversion of seismic and geoelectrical data and was applied to datasets from a test site in Cornwall, England, yielding improved models compared to separate inversions (Gallardo and Meju, 2003). This algorithm produced a significant degree of structural similarity between the resistivity and velocity models. Gallardo and Meju further employed the cross-gradient function for 3D joint inversion of magnetic and gravity data. In this approach, by incorporating a regularization parameter, models were obtained that showed improved lateral and depth consistency relative to independent inversions. Zhou and Owen (2015) proposed a similar algorithm in which normalized magnetic data were used. Cross-gradient–based joint inversion algorithms have been successfully applied to a wide range of geophysical datasets, resulting in models with enhanced structural similarity. Given that potential field data are often widely available over common survey areas, the application of cross-gradient joint inversion to gravity and magnetic data is of particular importance. Gross (2015) presented a weighted cross-gradient joint inversion of gravity and magnetic data in which by locally weighting the cross-gradient term, he significantly improved the structural similarity between the recovered density and magnetic susceptibility models. Bennington and Owen (2015) employed the cross- gradient constraint for the joint inversion of magnetotelluric and seismic data in Parkfield, California, to investigate the distribution and migration of fluids at both shallow and greater depths, achieving substantially improved structural similarity between resistivity and velocity models compared to separate inversions. Zhang and Wang (2020) proposed a joint inversion algorithm for gravity and magnetic data by minimizing an objective function composed of three terms: data misfit, a total variation stabilizer, and a cross- gradient constraint. Tavakoli, et al. (2021) proposed an algorithm for the joint inversion of gravity and magnetic data based on combining separate inversions with correction steps using a cross- gradient constraint within the joint inversion framework.

Methodology and Approaches

Gallardo and Meju (2003, 2004) formulated a framework for the joint inversion of two arbitrary geophysical methods using the cross-gradient constraint. When no explicit analytical relationship exists between the physical properties associated with different geophysical methods, joint inversion can be employed to obtain models that exhibit a relatively good degree of structural compatibility. Initially, the following relationship was used to quantify the structural dissimilarity between different geophysical images (Gallardo and Meju, 2004):

$$\theta(x,y,z) = \cos^{-1}\left(\frac{\nabla m_1(x,y,z)\cdot\nabla m_2(x,y,z)}{|\nabla m_1(x,y,z)|\ \ |\nabla m_2(x,y,z)|}\right) \qquad (1)$$

where ∇m_1 and ∇m_2 denote the gradients of different physical property models. According to the above expression, the denominator becomes zero at locations where either ∇m_1 or ∇m_2 vanishes; therefore, the cross-gradient function was introduced to avoid this singularity. This function is defined as the vector cross product of the gradients of the geophysical model parameters and is used to quantify the structural similarity between different geophysical model images:

$$\vec{t}(x,y,z) = \nabla m_1(x,y,z) \times \nabla m_2(x,y,z) \qquad (2)$$

This second-order nonlinear function does not suffer from the discontinuity and singularity problems associated with the angular function. When the value of this function is zero, the model images are structurally identical. In fact, a zero cross-gradient implies that the spatial variations in the two different geophysical models, regardless of their amplitudes, occur in the same direction; mathematically, the two vectors are parallel. From a geological perspective, this collinearity facilitates the identification of layer boundaries. Selecting an appropriate value for the regularization parameter is one of the key issues in regularization methods, including Tikhonov regularization (Oldenburg and Li, 2005). Tikhonov regularization is the most widely used approach for solving ill-posed problems. Numerous techniques have been proposed for choosing the regularization parameter in geophysical inversion problems, and depending on the conditions, these methods may yield either satisfactory or unsatisfactory solutions (Hansen, 2010). The regularization parameter satisfies $0 < \alpha < \infty$ and is also referred to as the balancing parameter. It controls the relative weighting between the data misfit term and the stabilizing functional. As α approaches zero, the minimized objective function consists solely of the data misfit term; consequently, the resulting model is constructed to fit the observed data as closely as possible. Conversely, when α is chosen to be large, the contribution of the data misfit term becomes small and the stabilizing functional dominates the minimization. Minimizing both the data misfit and stabilizing terms is essential for solving the inverse problem; thus, the role of the regularization parameter is to balance the relative importance of these two terms (Oldenburg and Li, 2005). The objective function for joint inversion using the cross-gradient constraint is formulated as:

$$\min\left\{\phi(m_1,m_2) = \left\| \begin{bmatrix} d_1 - A_1 m_1 \\ d_2 - A_2 m_2 \end{bmatrix} \right\|^2_{C_{dd}^{-1}} + \left\| \begin{bmatrix} a_1 D m_1 \\ a_2 D m_2 \end{bmatrix} \right\|^2 + \left\| \begin{bmatrix} m_1 - m_{R1} \\ m_2 - m_{R2} \end{bmatrix} \right\|^2_{C_{RR}^{-1}} \right\} \text{subject to } \vec{t}(m_1,m_2) = 0 \qquad (3)$$

Here, d_1 and d_2 are the logarithms of the observed data. A_1 and A_2 denote the forward operators, and C_{dd} is the covariance matrix of the measured data, which is assumed to be diagonal in this study, implying that the data are uncorrelated. The term $\vec{t}(m_1,m_2)$ represents the values of the cross-gradient function for all model cells. D is the regularization matrix, and a_1 and a_2 are regularization parameters that control the smoothness of the models. Finally, m_{R1} and m_{R2} are the reference models for the two methods, with covariance matrix C_{RR}.

Results and Conclusions

The real datasets used in this study correspond to the hematite–magnetite ore body at Gol-e-Gohar Mine No. 2 in Iran. The data were sampled on a 50 × 50 m grid. From a geological perspective, the Gol-e-Gohar mining district is entirely located within the southern segment of the Sanandaj–Sirjan Zone. The sampled gravity and magnetic data are on the 50 × 50 m. In the separate inversion of the datasets, the ore bodies tend to merge into one another, whereas the model recovered from the cross-gradient joint inversion exhibits a clearer separation of the bodies. Compared to the separate inversion, the joint inversion provides better performance in estimating the deeper parts of the model and completely

removes the spurious deep artifacts, while also fully compacts the model in the X and Y directions.
In this paper, 3D joint inversion of gravity and magnetic data using the cross-gradient constraint has been investigated. The performance and effectiveness of this approach have also been evaluated using a set of synthetic and field datasets. One of the main challenges in the separate inversion of potential field data is that the recovered models tend to be elongated in the x, y, and z directions, resulting in geometries that deviate from the true subsurface model. The results of the separate inversions indicate that the gravity model extends to depths of approximately 500 m, while the magnetic model reaches depths of about 600 m. In contrast, the joint inversion partially alleviates this problem: the recovered model becomes more compact in the x and y directions and is also more focused in the z direction, with the anomaly uplifted to a depth of approximately 300 m, showing better agreement with the true model and available drilling information from the study area. The results, obtained in this study, demonstrate that the joint inversion of potential field data using the cross-gradient constraint provides improved performance in estimating the model geometry as well as in reconstructing the physical properties of the subsurface. In other words, this approach is capable of yielding more accurate estimates of model parameters at greater depths. This method can mitigate one of the fundamental drawbacks of potential field data inversion, namely the downward smearing of anomalies and the poor resolution of the lower boundary of the target body.