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Gravity gradiometer data analysis in mineral exploration

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ABSTRACT

Gravity gradiometer surveys are becoming increasingly important in the search for and characterization of mineral deposits. Measurement of the full gravity gradient tensor provides the opportunity for processing and interpretation of single tensor components or combinations of components. To effectively use these components and combinations thereof, it is necessary to characterize the information content in order to interpret the gradiometer data correctly. We use linear inverse theory to evaluate different components and their combinations and find that which concatenated components produce the smallest modelling errors. Of the single tensor components, the Tzz component was found to provide the best performance overall. Since airborne gradiometer data are collected in a highly dynamic environment, noise is ever-present and must be compensated for to produce a clean signal for interpretation. Two approaches were investigated for removing noise: kriging and directional filtering. The kriging and directional filtering results show a similar level of smoothness, the main difference being the increased smoothing along strike of the directionally filtered data. Since kriging is a data-driven procedure, it provides an objective estimate of the data noise level and degree of smoothness. Based on the kriging results, processing parameters can be chosen to give a similar level of smoothness and noise suppression for directional filtering, that more effectively delineates geological trends in the data.

INTRODUCTION

Unlike gravity data, gravity gradiometer (GG) data comprise measurements of all components of the gravity field and provide greater sensitivity at shorter wavelengths, making them well suited for small-scale mineral exploration studies. Recently, the Geological Survey of Canada has collected GG data over several mineral prospects in Canada. To understand and effectively utilize these data, our studies had two main goals: (1) to quantify the information content in the different gravity gradient tensor components and (2) to suppress the noise in the measured data.

Methods of interpretation for GG data parallel those developed for gravity and magnetic data due to their similarities but gradiometer systems measure components that do not have an equivalent counterpart in gravity and magnetic interpretation. Qualitative methods, such as a simple visual inspection of all tensor components, are hindered by the complicated form of the non-Tzz components. Consequently, Tzz is usually the component of choice, especially for qualitative interpretation. Quantitative methods have been developed for GG data that use either single tensor components or combinations thereof (Vasco and Taylor, 1991; Zhang et al., 2000; Zhdanov et al., 2004; Beiki and Pedersen, 2010; Martinez et al., 2013). A quantitative comparison of tensor components and their combinations was made by Pilkington (2012), who utilized GG data to determine the densities within a three-dimensional (3-D) subsurface volume. Using a measure of information content commonly used in optimal survey design to rate different components (and some component combinations), Pilkington (2012) concluded that Tzz was the most useful single tensor component and that results could be improved by adding more components to the data vector. However, Pilkington (2012) did not consider data errors and the geometry of the model employed did not allow for investigation of individual model parameters and their effects on the components. Therefore, we used parametric inversion to evaluate tensor components and their combinations through inversions using models with only a small number of parameters. By analyzing the parametric errors generated by inversion of different tensor components and combinations, we evaluated the relative information content of the different data types.

Collecting gravity data in a dynamic environment, such as an aircraft, leads inevitably to the presence of noise in the measurements. The sources and approaches to treatment of noise in airborne gravity gradiometer systems are numerous and have been discussed extensively (e.g. Dransfield and Christensen,

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Table 1. Tensor components and component combinations used in this paper (notation *Tuv* | *Txy* means that, for example, data vectors *Tuv* and *Txy* both with length *n* are concatenated to form an augmented vector with length 2*n*).

No.	Description
1	Txx = Gradient in x direction of x-component of gravity field
2	Txy = Gradient in y direction of x-component of gravity field
3	Txz = Gradient in z direction of x-component of gravity field
4	Tyy = Gradient in y direction of y-component of gravity field
5	Tyz = Gradient in z direction of y-component of gravity field
6	Tzz = Gradient in z direction of z-component of gravity field
7	Tuv = = 0.5*(Txx-Tyy)
8	I1 = TxxTyy+TyyTzz+TxxTzz-Txy^2-Tyz^2-Txz^2
9	I2 = Txx(TyyTzz-Tyz^2)+Txy(TyzTxz-TxyTzz)+Txz(TxyTyz-TxzTyy)
10	H1 = sqrt(Txz^2+Tyz^2)
11	H2 = sqrt(Txy^2+0.25*$(Tyy-Txx)^2$)
12	C1 = Tuv | Txy
13	C2 = Txz | Tyz | Tzz
14	C3 = Txy | Tyz | Txz
15	C4 = Txx | Tyy | Txy
16	C5 = Tzz | Tyz | Txz | Txy | Txx
17	C6 = Tyy | Tyz | Txz | Txy | Txx

2013). Standard processing of GG data is designed to suppress the unwanted noise and emphasize the geological signals. Nonetheless, currently produced GG data often still contain high enough levels of noise to interfere with both qualitative and quantitative interpretations. Our approach was to explore several noise-reduction methods to determine their applicability and effectiveness in removing unwanted noise in GG data.

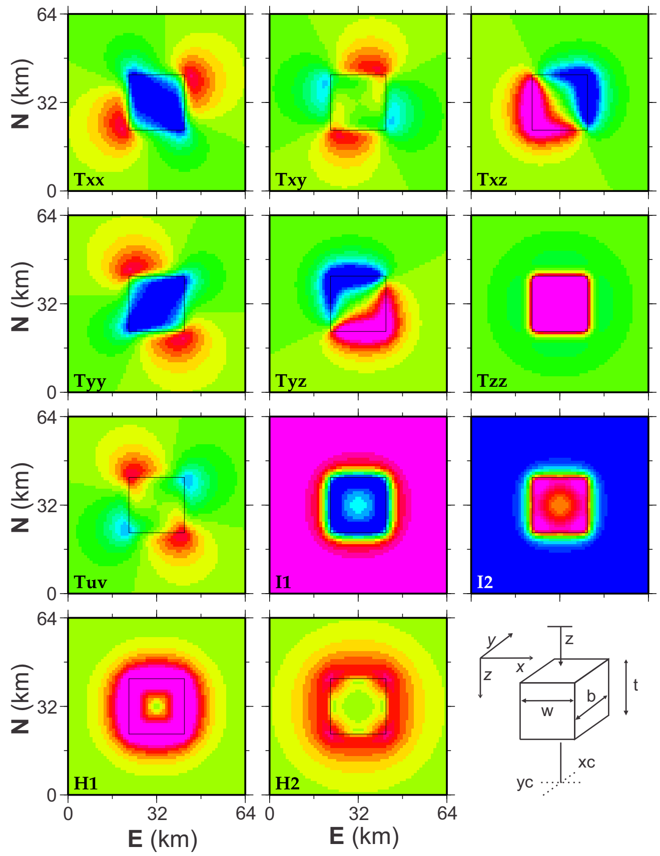

Figure 1. Component quantities from Table 1 (1 to 11) calculated over a single prism, with the measurement coordinate system rotated by 30º, which simulates a flight direction of N60ºE. Prism model parameters are z = 2 km, t = 8 km, w = 20 km, b = 20 km, ρ = 0.2 gcm^{-3}.

RESULTS

Evaluating Tensor Component Utility

The aim of this study was to use the estimated parameter errors resulting from inversions of single and multiple tensor components to quantitatively rate their information content. Table 1 gives a list of 17 different component quantities consisting of single tensor components (1 to 6), combinations of components (7 to 11), and concatenations of components (12 to 17); Figure 1 shows quantities 1 through 11 calculated for a prismatic model.

Linear inverse theory provides all the tools to examine the relationship between the different data types and the model parameters (Inman, 1975). A simple prism model (Fig. 1) was used, which was characterized by just seven parameters: xc and yc - the x and y coordinates of the prism centre; w and b - the prism width (in x) and breadth (in y); ρ - the density; z - the depth to the top surface; and t - the vertical thickness.

Once an inversion is completed, the errors in the model parameters can be estimated (Pilkington, 2014). A range of models was tested to determine how different component quantities affected parameter errors (see Table 2 for a list of parameter values). Varying parameters t, w, b, and z simulates shallow to deep prisms, and thin to thick plates and dykes. For each model, the standard deviations of the parameter errors were calculated. The resulting standard deviations were then ranked for each parameter by component quantity (Table 1), with a value of 1 assigned to the smallest parameter error and a value of 17 to the largest. Figure 2 illustrates the summing of the rank values for the 29 models (a high-ranking value is indicative of large parameter errors). Seven points are plotted for each component quantity, each corresponding to a single model parameter.

Figure 2 shows that most of the 17 component quantities have parameter rankings clustered fairly close together, i.e., none of the parameters are much more reliably estimated than the others. Tzz shows a lower ranking (lower error) than the other single components (Fig. 2). Some individual parameters are estimated to have lower errors than those generated using Tzz but these are limited to a few cases where parameters benefit from directional strengths in some of the single tensor components. The mainly horizontal component combinations H1 and C1 (Tuv | Txy, Table 1) are ranked at a similar level as Tzz. In contrast, the purely horizontal quantities H2, Tuv, and Txy have higher errors. These three components comprise just Txx, Tyy, and/or

Table 2. Values of the parameters used in the 29 models shown in Figure 2. Note: xc and yc are the x and y coordinates of the prism centre; w and b are the prism width (in x) and breadth (in y); ρ represents the density; z is the depth to the top surface; and t is the vertical thickness.

xc (km)	xc (km)	z (km)	t (km)	w (km)	b (km)	ρ (g/cm^3)
32	32	4	1,3,6,13,43	12	12	0.2
32	32	4	13	0.1,0.5,2,6,9	12	0.2
32	32	0.1,1,3,6,12	40	12	12	0.2
32	32	2	1	1	1	0.2
32	32	2	4	4	4	0.2
32	32	2	8	8	8	0.2
32	32	0.5,1,2	4	1	1	0.2
32	32	0.5,1,2,4	1	8	8	0.2
32	32	0.5,1,2,4	2	2	2	0.2

Txy. The invariants I1 and I2 are ranked between the lower ranked concatenated combinations and those discussed above. Both I1 and I2 have tightly clustered parameter rankings and have the lowest errors of the combined component quantities.

In agreement with Pilkington (2012), Figure 2 shows that the concatenated components have the lowest ranking, producing the smallest parameter error estimates. This demonstrates that when components are combined into a single quantity through multiplication and addition, it does not perform as well as if the same components are simply concatenated. For example, comparing H2 and C4 (Txx | Tyy | Txy combination, Table 1), they both contain the same (purely horizontal) components but provide very different error estimates, the latter having much lower errors. Component quantity C1 (Tuv | Txy, Table 1) is a mix of combination and concatenation, and has a ranking between H2 and C4 (Txx | Tyy | Txy, Table 1).

Noise Suppression for Gradiometer Data

Two approaches were considered for noise removal in GG data: kriging and directional filtering. Kriging is an estimation procedure commonly used in geostatistics for the interpolation of spatial data (Matheron, 1963) and provides the best linear unbiased estimator. A more detailed description of the method can be found in Keating and Pilkington (2013) and Pilkington and Shamsipour (2014). For the simple case of signal (gravity effects of geology) and uncorrelated noise, ordinary kriging provides an unbiased estimate of a noise-free signal and hence was chosen for use with the GG data.

Figure 3a shows a portion of the Tzz component from a GG data survey, illustrating the noisy character of this kind of data. The kriged data (Fig. 3b) shows a significant reduction in uncorrelated noise level, resulting in the appearance of more coherent gradient features throughout the area. With the suppression of shorter wavelength components, the kriged data are generally smoother than the gridded (minimum curvature) flight-line data (Fig. 3a). The kriged values are, nonetheless, optimal in the sense of being estimated from an interpolator based on the data themselves, and not from an arbitrary interpolator such as the minimum curvature operator. The difference between standard minimum curvature gridding (Fig. 3a) and kriging (Fig. 3b) is illustrated in Figure 3c, which shows the mostly uncorrelated noise components removed by the kriging method.

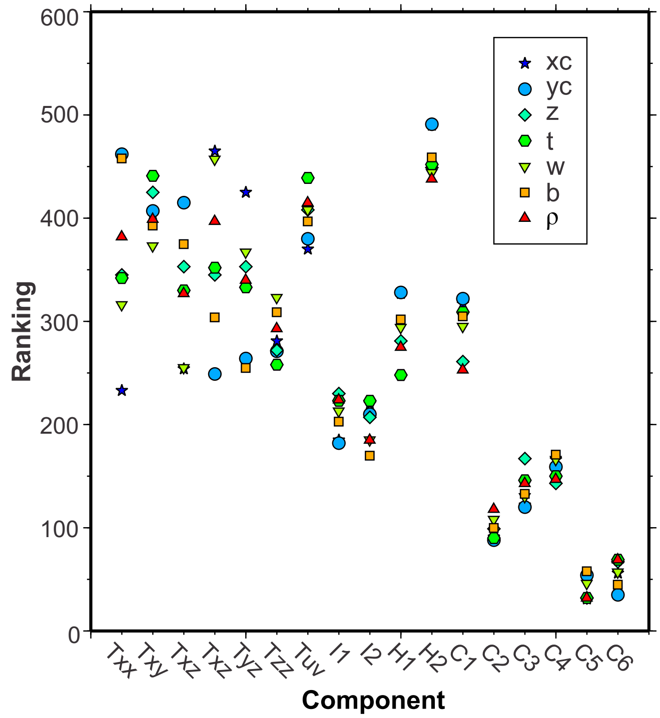

Figure 2. Parameter rankings versus component type based on 29 model inversions. For each inversion, the parameter standard deviations were ranked by component quantity (see Table 1), with a value of 1 assigned to the smallest parameter error and a value of 17 to the largest. Plotted values are the sums of the ranked values. High-ranking values are equivalent to large parameter errors.

The type of anomaly in GG data that is most useful for geological mapping is two-dimensional (2-D). Quasi-linear (2-D) features in the data may correspond to lithological contacts, but even if this is not the case, such trends can help in distinguishing structural regimes, and deformation styles and trends. Since a 2-D feature varies more smoothly along strike than perpendicular to strike, low-pass filtering to remove noise can be tuned to take this into account. Short-wavelength features can be removed preferentially along strike but preserved in the cross-strike direction. In this fashion, short-wavelength components that provide the detailed definition of the 2-D features are unaffected, whereas the short-wavelength noise that overprints and

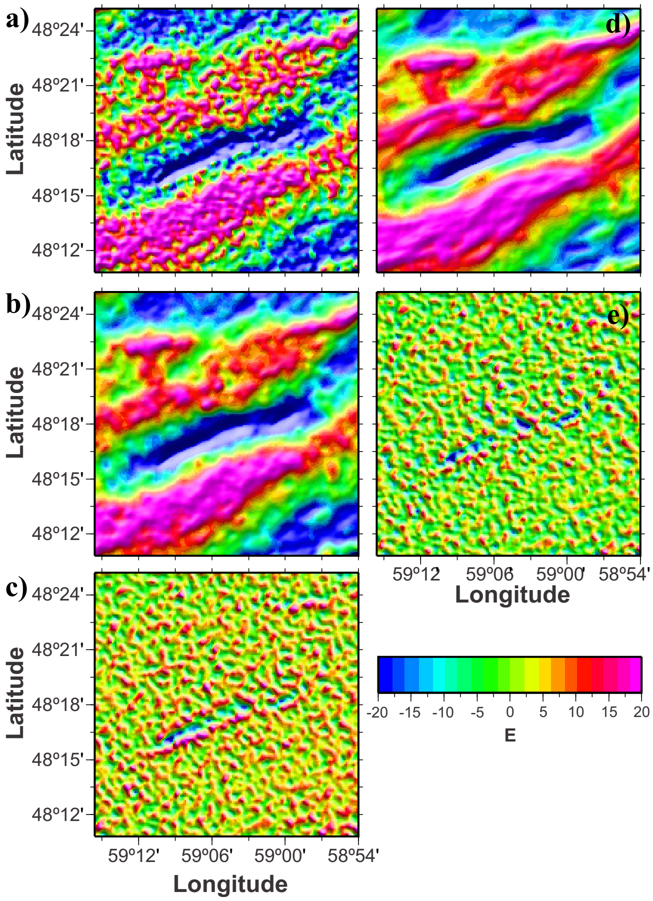

Figure 3. a) Original Tzz data from St. Georges Bay, Newfoundland and Labrador. **b)** Kriged data for the same area as (a). **c)** Difference between grids (a) and (b). **d)** Data from (a) directionally filtered. **e)** Difference between grids in (a) and (d).

disrupts along-strike trends is suppressed. This is the essence of directional filtering (e.g. Brewster, 2013). A directional filter requires the orientation or strike of the filter to be known at each grid point, which can be found from the two orthogonal horizontal gradients of the component.

Figure 3d shows the results of directionally filtering the data in Figure 3a. There is likely still some residual short-wavelength noise in the filtered grid, but through the smoothing effect of the directional filter the signal-to-noise ratio of the data is increased. Also, because the directional filtering uses the long-wavelength portion (assumed noise-free) of the input data to orient the smoothing, the short-wavelength trends are likely more reliable. Figure 3e shows the difference between the original (Fig. 3a) and directionally filtered data (Fig. 3d) for the Tzz component. The difference grid appears predominantly random, except for some coherent signals related to the strong ENE-WSW negative anomaly in the centre of the area. The kriging (Fig. 3b) and directional-filtering results (Fig. 3d) are not grossly different in appearance. The level of smoothness is similar and the main contrast between the two is the extra smoothing along strike for the directionally filtered data.

Kriging is computationally intensive, but almost completely data driven. On the other hand, directional filtering requires several user-defined parameters. A practical approach for noise reduction is to use kriging first and use the results to guide the choice of the parameters required in directional filtering. Kriging gives an estimate of how much noise is present and also specifies the correlation character of the data. The directional filtering can then be tuned to give a similar level of smoothness and noise suppression as the kriging results, but with the advantage of keeping more short-wavelength information in the cross-strike direction for better trend definition.

DISCUSSION

Using estimated parameter errors from parametric inversions allows for a quantitative ranking of single tensor components, combinations of components, and concatenations of components. Furthermore, linear inverse theory allows incorporation of the appropriate relative noise levels of the tensor components. Ranking of the estimated model errors from a range of model types shows that data sets consisting of concatenated components produce the smallest parameter standard deviations. Combinations of the purely horizontal components Txx and Tyy perform the poorest. Of the single tensor components, Tzz gives the best performance overall, but single components with strong directional sensitivity (e.g. Txx, Tyy) can produce some individual parameter estimates with smaller errors.

Both ordinary kriging and directional filtering are shown to be viable options for noise suppression in gravity gradiometer data. Kriging is based on the statistical character of the data and produces estimates with a commensurate level of smoothness and noise reduction. For directional filtering, the degree of smoothing is user-defined but has the advantage of being sensitive to strike information derived from the data. Both approaches successfully reduce noise levels so that coherent, geologically meaningful anomaly patterns are revealed.

IMPLICATIONS FOR EXPLORATION

The utility of gravity gradiometer data is dependent on both the quality of the data and also our understanding of what information the data contain. The development of practical ways of suppressing noise in GG data allows more effective presentations of the data for qualitative interpretation and provides more accurate input values into quantitative interpretation methods such as modelling and inversion. Determining the information content in the individual tensor components and their combinations can be a guide when selecting which tensor components should be used in an interpretation. GG data can provide a high-resolution gravity signal that, combined with co-located magnetic data, can provide an essential tool in Ni-Cu-PGE, Cr-PGE, and Fe-Ti-V exploration by identifying mafic and ultramafic prospective units within poorly exposed regions and also constitute important constraints in the modelling of individual geophysical anomalies directly related to magmatic ore deposits.

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