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Towards understanding the influence of data-richness on interpretational confidence in image interpretation

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SUMMARY

Geological interpretations of aeromagnetic and gravity images are highly subjective but are rarely accompanied by a quantitative confidence assessment, which is a key limitation on the usefulness of the results. This paper outlines a method with which the relative level of data richness can be assessed quantitatively, leading to an improved understanding of spatial variations in interpretational confidence. Simple rules were used to quantify the likely influence of several major sources of uncertainty. These were: 1) the level of geological constraint, using the local abundance of outcropping rock and the scale of geological mapping; 2) the interpretability of the data, considering the strength of edge-like features and the degree of directionality of these features; 3) data collection and processing errors, including gridding errors, and the influence of anisotropic line data collection on the detection of gradients. From these individual sources of uncertainty an overall data richness map was generated through a weighted summation of these grids. Weightings were assigned so as to best match the result to the interpreter's perception of interpretational confidence. This method produced a map of data richness, which reflects the opportunity that the data provided to the interpreter to make a correct interpretation. An example from central Australia indicated that the data influences were preserved over a moderate range of weighting factors, and that strong bias was required to override these. In addition to providing a confidence assessment, this method also provides a way to test the potential benefits of additional data collection.

Key words: interpretation, uncertainty, magnetic, gravity.

INTRODUCTION

The manual interpretation of geophysical images remains a very important method in exploration, and is one of the key means by which geological meaning is attached to the physical properties measured. In minerals exploration aeromagnetic and gravity data are most commonly interpreted in this way, and we focus on those data types.

Constrained qualitative interpretations are often extremely valuable for explorers to provide geological context under cover. However, to recognise their true worth it is important to map out, in some way, the level of confidence that exists in the interpretation.

Several approaches are possible, including quite generic discussion on the confidence in interpretation (e.g. Aitken and Betts 2009, Aitken, et al. 2008), through attributing interpreted features with a qualitative "confidence factor", through to more involved approaches using geostatistics, fuzzy logic, machine learning and information entropy (e.g. Knox-Robinson 2000, Wellmann, et al. 2010, Yamamoto, et al. 2012). Here, we seek an intuitive and quantitative method that can be easily applied using readily available tools and minimal computing resources.

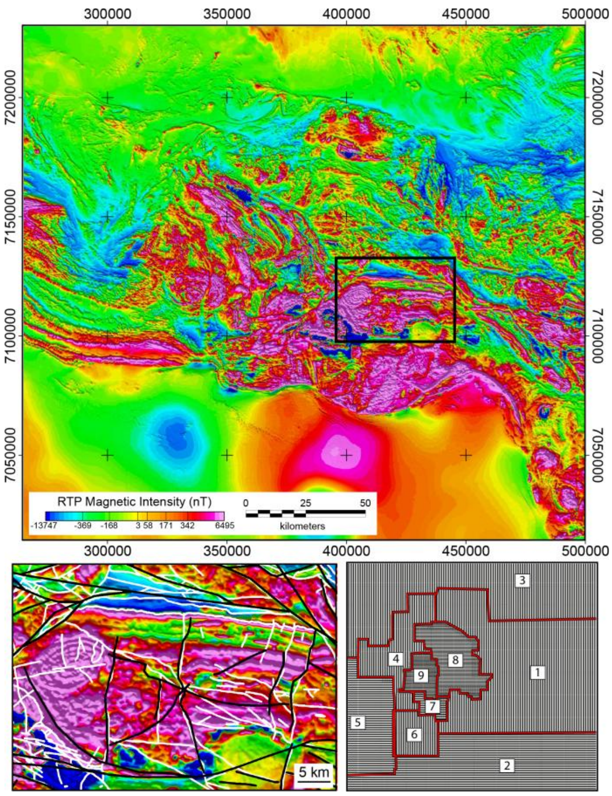

Figure 1. Aeromagnetic data in the sample area of the west Musgrave Province. Bottom left inset highlights the differences in interpretation of Joly et al. (2013) in black and Smithies et al (2009) in white. Bottom right inset indicates source surveys, stitching order and flight line orientations.

We separate interpretational confidence into "human-related" and "data-related" categories. The former category encompasses all prior knowledge, biases, preconceptions and inconsistencies that the human brings to the interpretation. These are somewhat understood (Bond, et al. 2007, Rankey and Mitchell 2003) but are hard to assess, and we leave this problem for future research.

Data related confidence factors include all the components in the data that may act to enhance or detract from interpretational confidence. These include the data distribution, signal amplitude, noise/error etc. In contrast to the human influences, these are often easily quantified and the cumulative effects can be assessed using a numerical approach

THE SAMPLE AREA

The sample area is the west Musgrave Province, an area where the aeromagnetic data were recently reinterpreted for the purposes of prospectivity analysis (Joly, et al. 2013). This area preserves a complex poly-deformational evolution (Smithies, et al. 2009) and this complex structuring is well imaged in the aeromagnetic data (Fig 1). A key challenge therefore is to unravel this high-level complexity, but to do so without over-interpreting structure in ill-constrained areas.

METHOD AND RESULTS

As noted above, we seek to characterise data-related influences on interpretational confidence. Conceptually, this can be thought of as estimating the opportunity the interpreter had to make a correct interpretation, rather than the correctness of the interpretation itself.

Here we focus on geologically constrained aeromagnetic interpretation, and identify the following sources of uncertainty:

1. The level of geological constraint.
2. The interpretability of the gridded aeromagnetic data.
3. Data collection and processing errors.

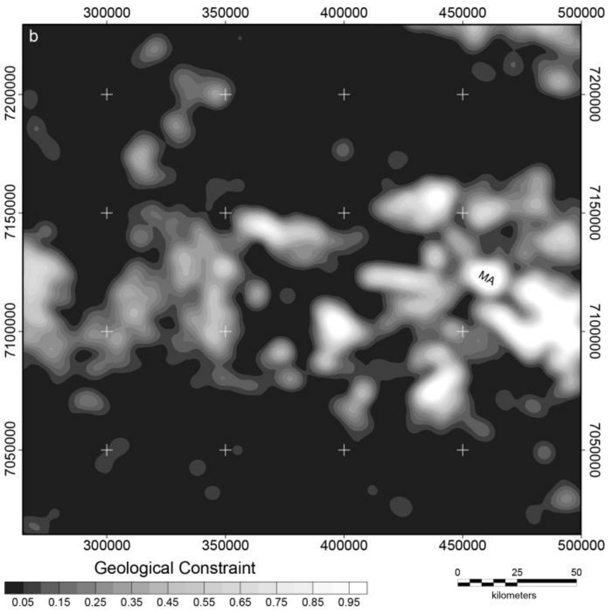

Figure 2. Geological constraint on the interpretation

For geological constraint, we take the geological maps of the area, and assign each outcrop an outcrop quality factor (the OQF). This OQF is based on factors such as the scale of geological mapping (1:100 000 vs 1:250 000), the age of the outcropping rock (Proterozoic vs Phanerozoic), and regions that are particularly well understood, for example due to detailed structural mapping (e.g. Mt Aloysius – MA (Fig. 2)). To provide a regional estimate, we then use a kernel density function (Silverman 1986) to estimate the combined influence of all outcrop within a certain radius, in this case 7.5 km (Fig. 2)

The level of interpretability of the gridded data is estimated considering two main factors. Firstly, the amplitude of "features" – i.e. ridges and edges – is estimated using a combination of a variety of edge detection filters. In this case we use the total horizontal gradient (Blakely and Simpson 1986), the standard deviation of texture (Holden, et al. 2008), the TDX filter (Cooper and Cowan 2006) and the phase congruency filter (Kovesi 1999). These are normalised to their 99th percentile, and combined through a simple weighted sum, to provide a feature strength map (Fig. 3) In this case equal weightings were preferred, but tests indicate the weightings are not especially influential.

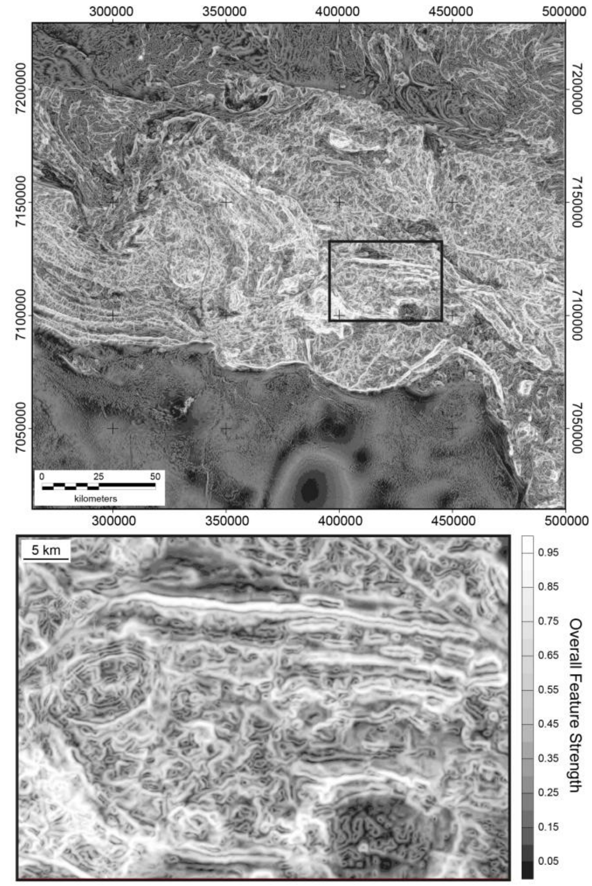

Figure 3. Feature strength map

We also consider the structural complexity of the aeromagnetic data, as poly-directional data are typically harder to interpret than mono-directional or non-directional data. We consider the level of data directionality as a proxy for complex structure. This is quantified using the orientation entropy approach of Holden et al (2012) based on the analysis of automatically picked structural elements. For the sample area, we use 8 orientation bins, sufficient to separate ENE from NE, and a window size of 3 by 3 km, which avoided over-averaging while capturing enough elements to provide a sound basis for the analysis (Figure 4).

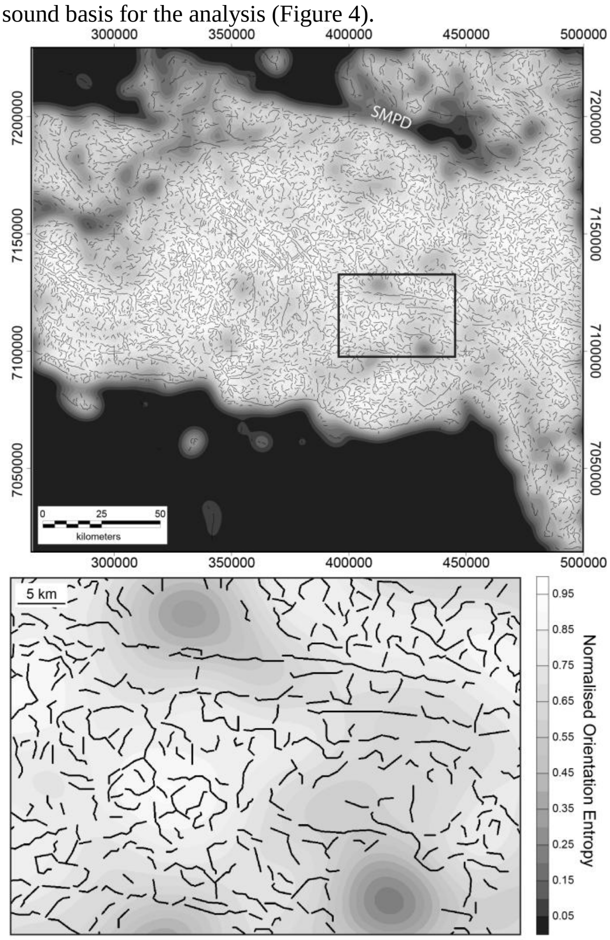

Figure 4. Structural Complexity Map

The final major component is data processing and collection errors. Here we focus on the gridding error, but also on the effect of anisotropic line-data collection in the imaging of gradients.

Gridding error is established statistically through kriging the data and returning the statistical error in the kriged grid. In this example, with fairly dense line data relative to the size of the region, the pattern of error varies quasi-linearly with the distance from the nearest line. Error is up to 100 nT between 200m spaced lines and 150 nT between 400m spaced lines.

The anisotropic sampling of conventional line-data presents a further complication, in that the horizontal gradient in the data will be less than the true gradient where the flight line is not perpendicular to strike. The observed gradient is given by the true gradient multiplied by the sine of the intersection angle. The effect of this can be assessed through computing the sines of the intersection angles between flight lines and the automatically picked structural elements, used previously in the orientation entropy calculation. We generate a grid for the mapping process by regionally averaging these point values within a certain radius of influence, in this case 2.5 km (Fig. 5). Mostly, fairly high values are returned (mean = 0.8), with only a few poor areas (e.g. Murray Range).

The final stage is to combine these individual factors into an overall map of data richness. For simplicity, this can be achieved as a simple weighted sum, according to the following equation:

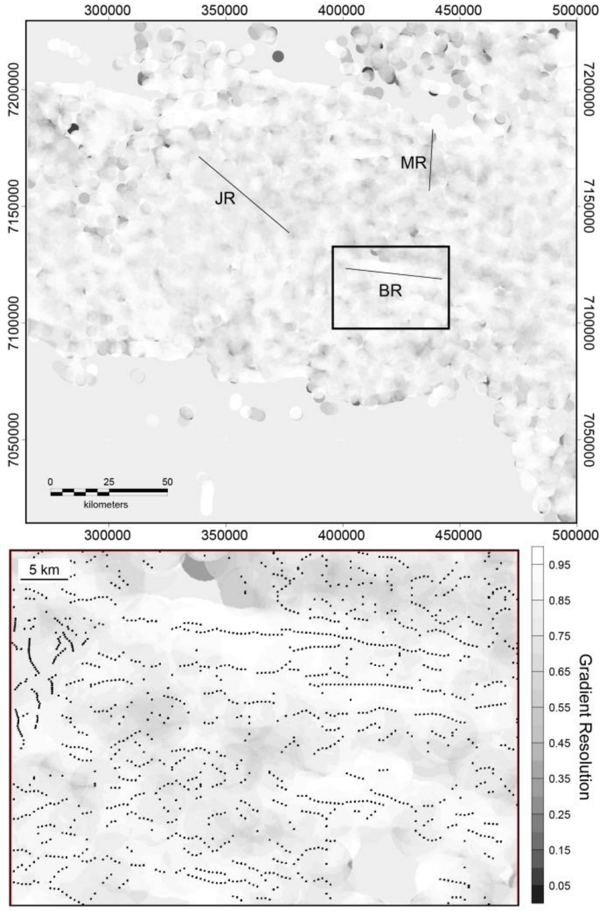

Figure 5. Line-anisotropy effect on gradient resolution

data richness =
w_1 * geological constraint
+ w_2 * (magnetic feature strength * sw_1 - sw_2*orientation entropy)
+ w_3* (anisotropy confidence * sw_1 - gridding error * sw_2)

Weightings and sub-weightings within this scheme must be subjectively assigned, so as to match the final product to the interpreter's perception of what was most influential in interpretational confidence. The final data richness map is shown in Fig. 6

In the case of the west Musgrave Province, the interpreter (Aitken) considered data interpretability to be most important (w_2=0.5), with geological constraint (w_1=0.4) being important also. Data processing errors were considered less important (w_3=0.1) due to the regional scale of interpretation, however for more local work these would perhaps be more important.
Within the data interpretability, feature strength dominated over orientation entropy (sw_1=0.8 vs sw_2 = 0.2) while in data processing, gridding errors were considered more important than anisotropy effects (sw_1=0.4 vs sw_2 = 0.6).

CONCLUSIONS

This method provides an easily applied method through which the influence of imperfect data on an interpretation can be assessed. This provides several key benefits

1. A guide to interpretation reliability for end users
2. Encourages critical thinking on interpretational confidence

3. Allows optimisation of the level of detail in the interpretation
4. Could assist in planning new data collection
5. Allows the propagation of interpretational confidence into any derivative products.

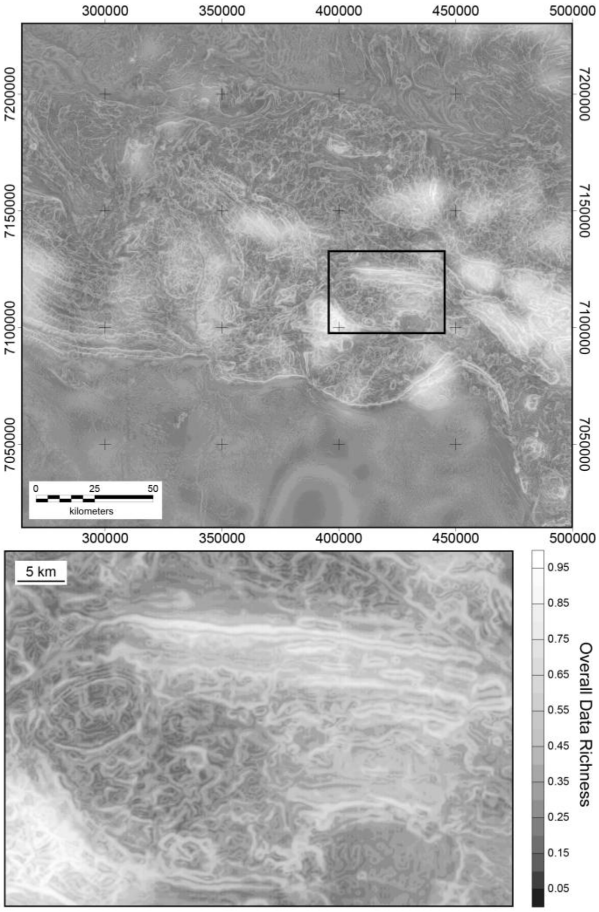

Figure 6. Final data richness map

This approach cannot account for human related influences, nor the complicated interplays between different data density in different data types that may lead to departures from the regional averaging. Nonetheless, our testing found that the results were robust under quite strong changes to the weighting scales and that a significant bias was required to override the data influences.

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REFERENCES

Aitken, A.R.A., and Betts, P.G., 2009, Multi-Scale Integrated Structural and Aeromagnetic Analysis to Guide Tectonic Models: An Example from the Eastern Musgrave Province, Central Australia. *Tectonophysics* **476**, 418-35.

Aitken, A.R.A., Betts, P.G., Schaefer, B.F., and Rye, S.E., 2008, Assessing Uncertainty in the Integration of Aeromagnetic Data and Structural Observations in the Deering Hills Region of the Musgrave Province. *Australian Journal of Earth Sciences* **55**, 1127-38.

Blakely, R.J., and Simpson, R.W., 1986, Approximating Edges of Source Bodies from Magnetic or Gravity Anomalies. *Geophysics* **51**, 1494-98.

Bond, C.E., Gibbs, A.D., Shipton, Z.K., and Jones, S., 2007, What Do You Think This Is? "Conceptual Uncertainty" in Geoscience Interpretation. *GSA Today* **17**, 4-10.

Cooper, G.R.J., and Cowan, D.R., 2006, Enhancing Potential Field Data Using Filters Based on the Local Phase. *Computers and Geosciences* **32**, 1585-91.

Holden, E.J., Dentith, M., and Kovesi, P., 2008, Towards the Automated Analysis of Regional Aeromagnetic Data to Identify Regions Prospective for Gold Deposits. *Computers and Geosciences* **34**, 1505-13.

Holden, E.J., Wong, J.C., Kovesi, P., Wedge, D., Dentith, M., and Bagas, L., 2012, Identifying Structural Complexity in Aeromagnetic Data: An Image Analysis Approach to Greenfields Gold Exploration. *Ore Geology Reviews* **46**, 47-59.

Joly, A., Aitken, A.R.A., Dentith, M., Porwal, A.K., and Smithies, R.H., 2013, Mineral Prospectivity Analysis of the West Musgrave Province, GSWA Report. Geological Survey of Western Australia.

Knox-Robinson, C.M., 2000, Vectorial Fuzzy Logic: A Novel Technique for Enhanced Mineral Prospectivity Mapping, with Reference to the Orogenic Gold Mineralisation Potential of the Kalgoorlie Terrane, Western Australia. *Australian Journal of Earth Sciences* **47**, 929-41.

Kovesi, P., 1999, Image Features from Phase Congruency. *VIDERE* **1**, 2-26.

Rankey, E.C., and Mitchell, J.C., 2003, That's Why It's Called Interpretation: Impact of Horizon Uncertainty on Seismic Attribute Analysis. *The Leading Edge* **22**, 820-28.

Silverman, B.W., 1986, *Density Estimation for Statistics and Data Analysis*. Chapman and Hall.

Smithies, R.H., Howard, H.M., Maier, W.D., and Evins, P.M., 2009, Blackstone, Wa Sheet 4545. *1:100000 Geological Series*, Geological Survey of Western Australia.

Wellmann, J.F., Horowitz, F.G., Schill, E., and Regenauer-Lieb, K., 2010, Towards Incorporating Uncertainty of Structural Data in 3d Geological Inversion. *Tectonophysics* **490**, 141-51.

Yamamoto, J.K., Mao, X.M., Koike, K., Crosta, A.P., Landim, P.M.B., Hu, H.Z., Wang, C.Y., and Yao, L.Q., 2012, Mapping an Uncertainty Zone between Interpolated Types of a Categorical Variable. *Computers and Geosciences* **40**, 146-52.