Sensitivity-based data reduction of large 3D DC/IP surveys

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SUMMARY

In this paper, we present an algorithm based on the sensitivity of the data to the model space to reduce the large amount of data commonly collected during 3D DC/IP surveys to only those most relevant and important to the model space. The sensitivity-based data reduction (SBDR) algorithm is demonstrated using both synthetic and field data examples. The results indicate that the SBDR recovered models are valid solutions to the full inversion problem but require a fraction of the computation time and resources, providing a geologic solution in a much shorter time than required to solve the full inversion problem.

Key words: 3D DC/IP; inversion; SBRD

INTRODUCTION

Geologic units have an inherent conductivity and chargeability that can be diagnostic in mineral exploration. Resistivity is the inverse of conductivity and both terms are used in this paper. Geophysical methods that are sensitive to conductivity and chargeability contrasts can be used to detect and map these contrasts and the results interpreted to advance problems in mineral exploration. One such method is the DC resistivity and induced polarization (DC/IP) survey. DC/IP surveys have been used to delineate many types of mineralization including: porphyry copper, vein-hosted gold, and uranium.

A typical DC/IP survey consists of two current electrodes and two potential electrodes organised in a linear array. The voltage is measured at the potential electrodes during the on-time portion of the current cycle to determine resistivity while IP measurements are made during the off-time portion. Traditionally, the electrodes are positioned along a line and multiple co-linear lines make up a survey block. More recently, 3D DC/IP surveys are increasingly gaining favour over the traditional 2D approaches. The 3D surveys provide large amounts of information about the subsurface, are not limited to parallel survey lines, and may be more effective in complex geologic settings where there is no clear geologic strike to allow optimal orientation of the 2D arrays. However, the relatively complex electrode distributions and the large volume of data acquired in 3D surveys make visualization of results relatively difficult. In traditional 2D surveys, the apparent resistivity and chargeability results are presented as 2D pseudo-sections and the data then inverted to generate resistivity and chargeability earth models for interpretation. The inversion of 3D surveys is complicated by the requirement of large meshes to accommodate the volume and density of data acquired. As a result, the computation time can become very significant and potentially inhibitive.

There is merit to reducing the complexity of 3D DC/IP datasets prior to inversion to test inversion parameters efficiently, to ensure the data quality control is satisfactory, and to obtain a model in a reasonable amount of time. Large 3D datasets may also contain highly redundant information and inputting this to the inversion process may not add to the accuracy of the recovered model.

Inversions perform best when the data has approximately uniform coverage (all parts of the model are represented approximately uniformly in the dataset). Non-uniform coverage may result from a survey design that includes directional bias or oversampling in one region and under-sampling in another. The acquisition of data using a survey design with directional bias and under-sampling compromises the value of the dataset. The acquisition of redundant data through over-sampling may not similarly compromise the value of the dataset but rather results in a waste of resources in both the field and in the office driving up the acquisition and processing costs.

In order to address the latter problem (to combat the issues presented when inverting large 3D DC/IP datasets), we propose a sensitivity-based data reduction (SBDR) algorithm that systematically reduces data volumes while minimizing information loss. In this paper, we present the algorithm, followed by synthetic and field examples.

METHOD AND RESULTS

Consider a uniform half-space earth with a conductivity (σ). A current (I) is injected into the homogeneous earth and the potential (V) is measured a distance (r) away from the current injection. The potential is then given by the equation

$$V(r) \approx \frac{1}{2\pi\sigma r} \quad (1)$$

A small conductivity perturbation ($\Delta\sigma$) is added to the uniform halfspace, as shown in Figure 1, which gives rise to a small perturbation in the measured potential. To account for this perturbation, a second term is added to Equation (1):

$$V(r) \approx \frac{1}{2\pi\sigma r} - \Delta\sigma \frac{1}{4\pi^2\sigma^2} \int_{\Delta v} \frac{\boldsymbol{r_1} \cdot \boldsymbol{r_2}}{r_1^3 r_2^3} dv \quad (2)$$

The second term in Equation (2) defines the sensitivity of the measured potential to the perturbation:

$$\frac{\partial V(r)}{\partial \sigma} = -\frac{1}{4\pi^2\sigma^2} \int_{\Delta v} \frac{\boldsymbol{r_1} \cdot \boldsymbol{r_2}}{r_1^3 r_2^3} dv \quad (3)$$

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We can then define the relative sensitivity (J) to be the sensitivity from Equation (3) normalized by the potential measurement:

$$J = \frac{1}{V(r)} \frac{\partial V(r)}{\partial \sigma} \quad (4)$$

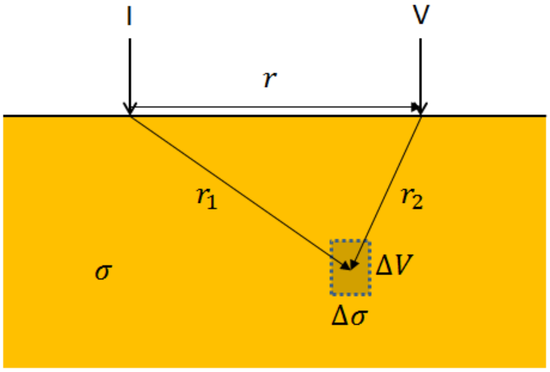

Figure 1. A current (*I*) is injected into a uniform halfspace earth (*σ*) with a small conductivity perturbation (*Δσ*). The potential (*V*) is measured a distance (*r*) away from the current injection.

The resistivity model space is discretized into a voxel mesh prior to inverting the data. To apply the SBDR algorithm, the relative sensitivity from Equation (4) is calculated at each voxel in the model for every measurement in the survey. The relative sensitivity values from each voxel are compared and only those data points that produce a large relative sensitivity are kept. Iterating over this for each voxel creates the reduced dataset based on the relative sensitivity.

This method separates data that have larger influence on the model, termed "relatively important" data, from those that have a lesser impact. The size of the reduced data set is controlled by the threshold on the relative sensitivity measured at each voxel. The size and distribution of the voxels can be used to control the degree of data reduction. A natural choice for the voxel size might be the desired conductivity resolution or a voxel size that is appropriate for the survey parameters.

An additional feature of this algorithm is that it can be used to specifically focus on a subdomain of interest. The numerical implementation can incorporate more complexity than a homogeneous model space; indeed, any a priori physical property information (i.e., a conductive overburden) may be included.

While the idea is quite simple, we have found it to be extremely effective, particularly in situations where alternative data reduction methods (i.e., subsampling) cannot be used (as is the case for 3D DC/IP or EM problems).

SYNTHETIC EXAMPLE

The SBDR algorithm is illustrated using a synthetic example where two 200 Ω-m prisms are buried in a 1,000 Ω-m background. A multi-line east-west oriented 2D dipole-dipole survey is collected at the surface. The electrodes have an a-spacing of 25 m and voltage data are measured at n=1 to 12, providing a relatively dense dataset. Figure 2 shows the electrode layout and the two conductive prisms.

The data were forward modelled and the full dataset inverted. We then applied the SBDR algorithm to select the "relatively important" data for the forward modelled dataset, resulting in a 50% reduction in the size of the dataset. These relatively important data were then inverted again using the same parameters as the inversion of the full dataset. Figure 3 compares the results between the full and reduced datasets, along with the data distribution. The two conductive prisms are nicely recovered in the correct locations in each inversion.

As mentioned above, the SBDR algorithm can also be used to focus the data on a certain region of the model. Figure 4 shows the results for a model sub-domain outlined in white (i.e., a possible target volume of exploration interest). The SBDR algorithm was used to only retain those data that have "relative importance" for the sub-domain. The model shows that the prism of interest is recovered while other features are not.

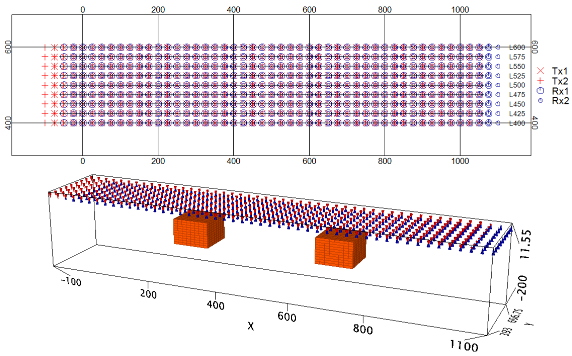

Figure 2. (top) A multi-line east-west oriented 2D dipole-dipole survey. Transmitters and receivers are indicated in red and blue, respectively. (bottom) The synthetic model consists of two conductive prisms buried in a uniform background.

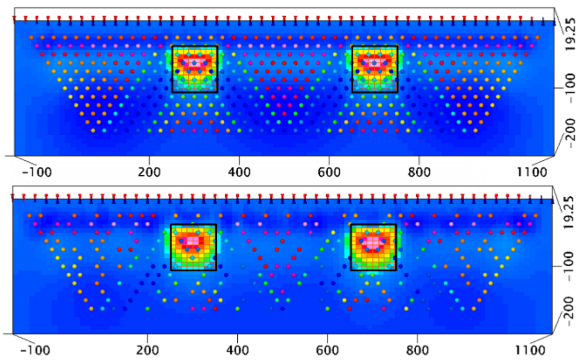

Figure 3. (top) The data are plotted as a pseudo-section with points, showing the full distribution, over a slice through the recovered model using the full dataset. (bottom) The points show the distribution of the "relatively important" data as a pseudo-section over a slice through the recovered model using the reduced dataset. In both panels, the true locations of the prisms are outlined in black. Blue colours indicate resistive areas while red colours indicate conductive areas.

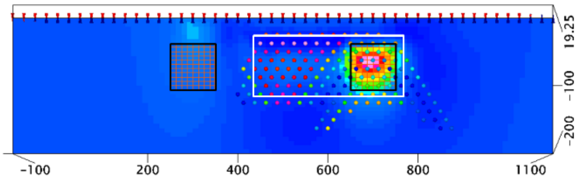

Figure 4. The SBDR algorithm is used to focus the data onto a sub-domain (indicated in white). The recovered model only produces the conductive prism inside the sub-domain. The true locations of the two prisms are outlined in black. Blue colours indicate resistive areas while red colours indicate conductive areas.

FIELD EXAMPLE

We showcase the SBDR algorithm on a field example. The DC/IP survey was collected over a known uranium occurrence in the Athabasca Basin of northern Saskatchewan, Canada, to define variations in resistivity correlated with mineralisation. The highly heterogeneous nature of the geology merits a 3D approach for the DC/IP survey.

The dataset consisted of approximately 470,000 pole-dipole voltage measurements, collected in a 3D orientation (Figure 5). Given the survey parameters, the inversion mesh would require 1.2 million voxels, which, combined with half a million measurements, was not feasible given our computation resources. In order to invert the full dataset, the model space had to be divided into 3 overlapping tiles. This method still took an unreasonable computation time as well as inducing some artefacts where the tiles overlap.

Because 3D DC/IP surveys could have electrodes that are far apart but still produce significant data, a tiled approach may not work for every type of survey without blindly removing data that extends outside each tile.

The SBDR algorithm was applied to the field dataset with two goals in mind: (1) invert the data on a single mesh, and (2) invert the data in a reasonable length of time. The algorithm reduced the full dataset of 470,000 measurements to approximately 70,000 "relatively important" data which could be significantly more easily be inverted on a mesh containing 1.1 million voxels.

The recovered model using the reduced dataset (shown in Figure 6) not only fit the observed data (reaching a reduced chi-square value of 1 using a data uncertainty of 5% plus a noise floor of 3 mV) but was consistent with the expected geologic structures and previously recovered conductivity models using other methods.

Our final question was if the SBDR recovered model was also an acceptable solution for the full dataset. This was tested by forward modelling the SBDR recovered model using the full dataset locations and comparing this predicted dataset with the full observed dataset. The reduced chi-square fit between the full observed and predicted data was 0.8, which is a reasonable data fit. This indicates that the SBDR recovered model is a valid solution to the full 3D inversion problem in this case.

Using SBDR to reduce the dataset allowed us to recover a conductivity model in 10 hours, which is a tremendous improvement in computational efficiency compared with the tiled inversion of the full dataset, which took approximately 50 hours.

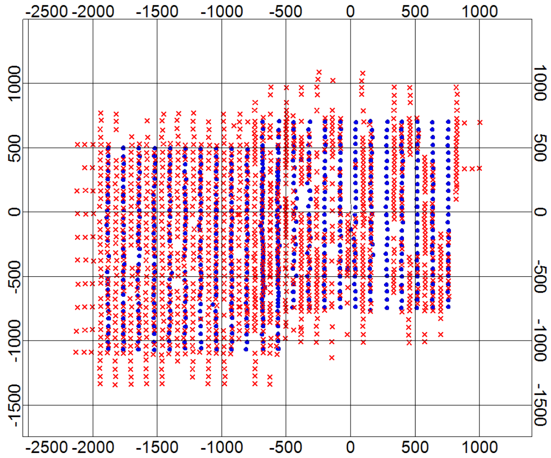

Figure 5. Distribution of electrodes in the 3D DC/IP survey. Transmitters and receivers are shown as red and blue dots, respectively.

CONCLUSIONS

In this paper, we presented a sensitivity-based data reduction algorithm to significantly reduce the number of DC/IP data required to generate a geologically reasonable inversion model from 2D synthetic and 3D field datasets. The SBDR approach was used to calculate those data which are "relatively important" in each dataset. The synthetic example showed that using the reduced data had no significant impact on the final model outcome.

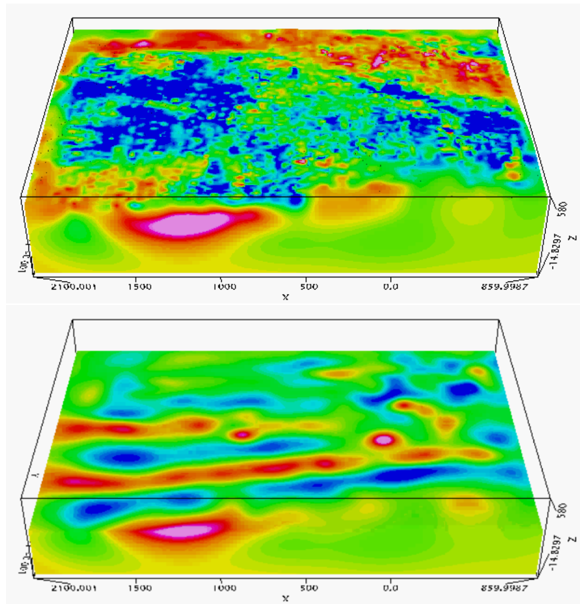

Figure 6. Recovered conductivity model using the 70,000 "relatively important" data at (top) the surface and (bottom) ~300 m constant elevation slice. Blue colours indicate resistive areas while red colours indicate conductive areas.

The use of the algorithm on the field dataset allowed us to find a solution in 10 hours. A direct inversion of the full dataset would have required at least several days using equivalent computer resources. The SBDR algorithm allowed us to

dramatically reduce the size of the dataset and consequently reduce the time and cost of the inversion problem. The results showed that the SBDR recovered model for the field example was also a valid solution to the full inversion problem.

By saving both time and computation costs, the user can now practically run more inversion trials, as very rarely does the first inversion produce the final model to be interpreted. Several trials allow the user to determine the best inversion parameters as well as data uncertainty assignments, and ultimately come up with the best possible solution for a geologic problem. The SBDR algorithm aids in allowing that process to occur in a reasonable time-frame for a mineral exploration program.

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