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Integration of Geophysical and Petrophysical Data Through Joint Inversion

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ABSTRACT

Geophysical inversion has proven to be an effective tool for extracting useful information about the subsurface in the mining industry. As mineral exploration increasingly focuses on deeply buried targets in geologically more complicated areas, it has been recognized that inversion of geophysical data needs to be constrained by geological data in order to be meaningful. Considerable efforts have been devoted to the development of new tools for constrained geophysical inversions. In this paper, we summarize our recent work on joint inversion of geophysical and statistical petrophysical data, and present two case studies that illustrate the use of this joint inversion approach as a direct imaging tool and an iterative hypothesis testing tool.

INTRODUCTION

One of the major tasks for earth scientists is to construct a 3D Earth model that is consistent with all existing geophysical and geological data as well as perceptions of the subsurface geology and mineralogy. Geophysical inversion has proven particularly useful for this purpose because of its ability to generate a 3D model or a suite of models from a set of observed geophysical data. Many inversion algorithms and tools have been developed and widely used in mineral exploration industry. However, the inversion of geophysical data must be constrained by geological data in order to be geologically meaningful and useful. This is especially true now as mineral exploration activities are moving towards targets under cover. Developing inversion algorithms capable of incorporating different types of geological information has been an active area of research in the past decade.

One type of geological data that can be incorporated into geophysical inversion is physical property measurements, or synonymously, petrophysical measurements. There are two types of petrophysical data: spatial petrophysical data and statistical petrophysical data. Spatial petrophysical data are linked with spatial locations (i.e., each datum is connected to a specific location in an area of study). Statistical petrophysical data only provide a statistical description about the distribution of the physical property values. In this case, the value of a physical property, such as density value, is considered as a random variable without specific connection to spatial locations. For example, statistical petrophysical data may tell us the number of possible rock types in an area and the mean density value for each rock type without reference to a particular location. Effective use of spatial petrophysical data in an inversion can be achieved by designing a detailed reference model (e.g., Farquharson, 2008; Williams, 2008) and creating spatially varying lower and upper bounds (e.g., Williams et al., 2016). However, the use of statistical petrophysical data in a deterministic inversion remains as a great challenge.

Recently, Sun and Li (2015, 2016, 2017) propose the use of fuzzy c-means (FCM) clustering for incorporating statistical petrophysical data into geophysical inversion. In this paper, we summarize the clustering inversion approach and present two case studies that demonstrate the use of clustering inversion in different petrophysical scenarios. In the first case study, adequate and reliable physical property measurements were made, and consequently, well defined petrophysical relationships between density and susceptibility values were established and directly incorporated into inversion. For the second example, however, petrophysical data were limited and were not considered as representative of the subsurface rock properties. The clustering inversion was then used as a hypothesis testing tool, instead of a straightforward imaging tool, to iteratively advance our understanding of the subsurface geology.

METHODOLOGY

The clustering inversion is able to invert petrophysical data and allow them to directly contribute to the construction of physical property models in the same way as geophysical data. It, therefore, represents a powerful way of integrating geophysical and petrophysical data in a common scheme. The clustering inversion can be applied to both a single type of geophysical data and multiple types of geophysical data, such as gravity and magnetics. In this contribution, we focus on the latter application, and refer to it as joint clustering inversion henceforth. Below we briefly review the joint clustering inversion algorithm and discuss its use as a direct imaging tool and a hypothesis testing tool.

Joint Clustering Inversion: Algorithm

The general form of the objective function for joint clustering inversion is summarized below:

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$$\varphi(\boldsymbol{m}_1,\boldsymbol{m}_2;u_{jk},\boldsymbol{v}_k)=\varphi_{d1}(\boldsymbol{m}_1)+\beta_1\varphi_{m1}(\boldsymbol{m}_1)$$
$$+\varphi_{d2}(\boldsymbol{m}_2)+\beta_2\varphi_{m2}(\boldsymbol{m}_2) \qquad (1)$$
$$+\lambda\left(\sum_{j=1}^{M}\sum_{k=1}^{C}u_{jk}^{q}D(\boldsymbol{y}_j,\boldsymbol{v}_k)+\sum_{k=1}^{C}\eta_k\left\|\boldsymbol{v}_k-\boldsymbol{t}_k\right\|_2^2\right)$$

where $\boldsymbol{m}_1$ and $\boldsymbol{m}_2$ are the two unknown physical property vectors sought by inversion, φ_{d1} and φ_{d2} are the standard data misfit terms for the two types of geophysical data, and φ_{m1} and φ_{m2} are the regularization terms with regularization parameters of β_1 and β_2, respectively. Parameters M and C represent the number of model cells in a spatial domain, and the number of expected clusters in a parameter domain (e.g., in a crossplot). The last two terms in equation (1) determine how the inverted physical property values cluster in a parameter domain. A larger value for λ results in more compact clustering features among jointly inverted physical property values, while a smaller value for λ allows for more scattering. The last term in the above objective function measures the closeness between the inverted cluster centres, $\boldsymbol{v}_k$, and the true (or the target) cluster centres, $\boldsymbol{t}_k$, as determined from the a priori petrophysical data. Here, membership value u_{jk} can be practically interpreted as the probability of the *j*'th model cell belonging to the *k*'th lithological unit. The parameter *q* controls the fuzziness of the membership values, and is typically set to 2.0. There is also a distance measure $D(y_j,v_k)$ in the above objective function. There are many different options for distance measures, such as Euclidean and Mahalanobis distance. We note that the choice of distance measure should reflect the shapes of the clusters (e.g., circular, elliptical, linear, exponential, etc.) existing in the available petrophysical data. We refer readers to Sun and Li (2017) for a full treatment of the distance measures.

The formulation of the objective function in equation (1) is driven by three motivations: (1) the inverted models should honor the observed geophysical data (through the data misfit terms), (2) the inverted models should show continuity or smoothness of physical property values in a spatial domain (through the two regularization terms), and (3) the inverted physical property values should exhibit certain types of clustering features in a parameter domain (through the last two clustering terms). We point out that, during joint clustering inversion, four quantities, $\boldsymbol{m}_1$, $\boldsymbol{m}_2$, u_{jk} and $\boldsymbol{v}_k$ are updated at each iteration and are output at the end of an inversion.

Joint Clustering Inversion: A Direct Imaging Tool

The joint clustering inversion method described above can be used as a direct imaging tool, i.e., a tool for imaging the Earth by estimating a spatial distribution of physical properties of interest (i.e., $\boldsymbol{m}_1$ and $\boldsymbol{m}_2$ in equation (1)), and/or by delineating a spatial distribution of different geological units (i.e., u_{jk} in equation (1)). It is usually a geophysicist's job to obtain physical property models, and a geologist's job to interpret the geological units based on a given physical property model. In practice, these two tasks are performed by these two groups of earth scientists mostly independently. The joint clustering inversion, however, can accomplish these two goals simultaneously, because it outputs both physical property models (i.e., $\boldsymbol{m}_1$ and $\boldsymbol{m}_2$) and a geological classification model (i.e., u_{jk}) in the end. It, therefore, serves to promote greater levels of collaboration between geophysicists and geologists.

We incorporate a priori petrophysical data into an inversion by (1) assigning a proper value to *C*, the expected number of distinct geological units, (2) carefully choosing distance measures based upon the shapes of the clusters observed in the measured physical property values, and (3) specifying target cluster centres, $\boldsymbol{t}_k$. In the case of circular clusters and elliptical clusters, these target cluster centres are essentially the average physical property values for the *k*'th geological unit. Accurately specifying these parameters requires a set of reliable petrophysical measurements over many rock samples that are representative of the geology in an area of study. That is, the features observed in the measured petrophysical data fully capture and reflect the true geology. This usually happens in brownfield exploration.

Joint Clustering Inversion: A Hypothesis Testing Tool

In practice, there are situations in which we may not have such quality petrophysical data. For example, the measured values only reflect some of the geological units; the physical properties for some of the geological units are missing. Or, we may only have rough estimates of the average of the physical properties for the subsurface rocks based on limited petrophysical measurements, previous studies, or even a textbook. This is usually the case for greenfield exploration. In such situations, the use of the joint clustering inversion as a direct imaging tool is hindered by the limited amount of petrophysical data.

However, by making different hypotheses about the petrophysics, the joint clustering inversion turns out to be a powerful hypothesis testing tool. The procedures for the hypothesis testing are summarized as follows. We start with a joint clustering inversion with all the available petrophysical information incorporated by minimizing the objective function in equation (1). If the resulting physical property models are able to reproduce the observed geophysical data, and are consistent with known geology, then the assumed petrophysical information is considered valid and representative of the study area. Otherwise, we make adjustments to the assumed petrophysical knowledge (i.e., propose a different hypothesis about the petrophysics), carry out a second joint clustering inversion accordingly, and check if the estimated physical property models are supported by all existing geophysical, geological and petrophysical data. This iterative process of testing different hypotheses continues until a hypothesis results in physical property models that are consistent with all available information.

This hypothesis testing process makes full use of the capability and flexibility of the joint clustering inversion, as summarized by equation (1), to incorporate different types of petrophysical data, and allow geologists to test different assumptions based upon their perceptions, even in the absence of solid petrophysical measurements.

In the remainder of this article we present two case studies that illustrate the use of joint clustering inversion as a direct imaging tool and a hypothesis testing tool.

FIELD DATA EXAMPLE

The first field data example consists of gravity and magnetic data as well as a set of petrophysical measurements. These petrophysical data were collected from 111 rock samples that are representative of the rock types in the area of study, and truly reflect the subsurface geology. Therefore, in the first example, we directly incorporated the available petrophysical data into joint clustering inversion of gravity and magnetic data, and generated images of the target.

In the second example, the petrophysical data consist of the average density and susceptibility values for the major rock types in the study area, and only represent an over-simplified summary of the petrophysical situations. We therefore put forward several different petrophysical hypotheses and tested each one of them until the proposed hypothesis resulted in physical property models that can explain all the available geophysical, geological, and petrophysical data.

Direct Imaging of Gabbro Intrusions

The study area is located near the town of Boden, Sweden. The objective of the geophysical surveys was to image the gabbro intrusions which can host copper, nickel and platinum group element minerals. The bedrock comprises metasupracrustal and plutonic rocks of Paleoproterozoic age. The petrophysical measurements are summarized in Figure 1.

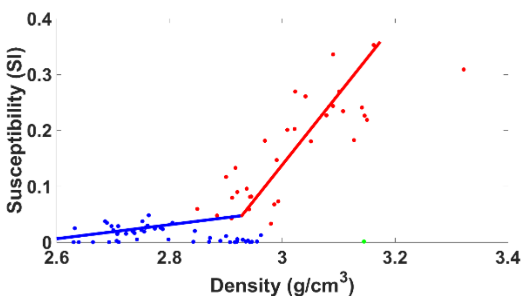

Figure 1: Density and susceptibility measurements from 111 rock samples. Red dots represent measurements from gabbro intrusions, and the blue from country rocks. The measured physical property values show two linear trends marked by the blue and red lines.

We performed joint clustering inversion by minimizing the objective function in equation (1) with C = 2, $\mathbf{t}_1$ = [0.005 g/cm^3, 0.0214 SI], and $\mathbf{t}_2$ = [0.275 g/cm^3, 0.1714 SI]. We chose the Mahalanobis distance measure in order to capture the correlations between density and susceptibility values that are readily observed in Figure 1. The jointly inverted density and susceptibility models displayed in Figure 2a and 2b reproduce their respective observed geophysical data adequately. We observe a compact anomalous feature in both models that corresponds to the gabbro intrusions. The shape and the location of the anomalous density body are highly comparable with those of the anomalous susceptibility body. The jointly inverted density and susceptibility values, shown as blue dots in Figure 2c, also exhibit two linear trends that are highly consistent with the measured physical property values (summarized by the two red lines in Figure 2c).

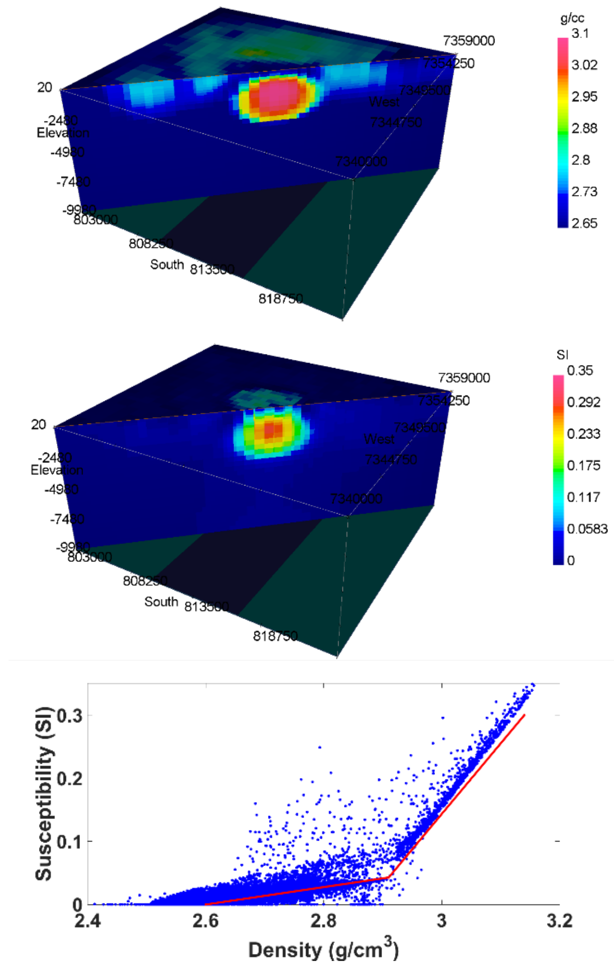

Figure 2: a) Density model recovered from joint clustering inversion. b) Susceptibility model recovered from joint clustering inversion. c) Jointly inverted density and susceptibility values in blue. The two linear trends observed in Figure 1 are marked in red.

In this example, we were able to image the gabbro by integrating the measured geophysical data and petrophysical data into joint clustering inversion. The obtained images of the gabbro intrusions are consistent with known geology and previous studies (Kamm et al., 2015).

Hypothesis Testing at a Sulphide Deposit

The gravity and magnetic data were collected over the Stratmat Main Zone copper-lead-zinc deposit in the south of the Bathurst Mining Camp in New Brunswick, Canada. The diamond drill holes revealed four major lithologic units: massive sulphides, volcanic tuffs, metasedimentary rocks and mafic intrusions (Mwenifumbo et al., 2003). Table 1 summarizes the average density and magnetic susceptibility values for each lithologic unit from rock sample measurements.

Lithology	Density (g/cm^3)	Suscep. (10^{-3} SI)
Mafic intrusion	2.66	6.38
Metasediments	2.70	6.09
Felsic tuff	2.60	6.12
Massive sulphide	3.61	81

Table 1: Average density and magnetic susceptibility values for each lithologic unit. This is our first petrophysical hypothesis.

The petrophysical data in Table 1 clearly show that the sulphide deposit has much higher density and susceptibility values than the other rocks. Thus, the sulphide deposit should be responsible for the observed gravity and magnetic anomaly. If we consider a cluster as the collection of lithological units having similar physical properties, then Table 1 suggests there are only 2 circular clusters in the study area. One cluster is characterized by high density and susceptibility values and corresponds to the sulphide deposit. The other cluster contains low density and susceptibility values.

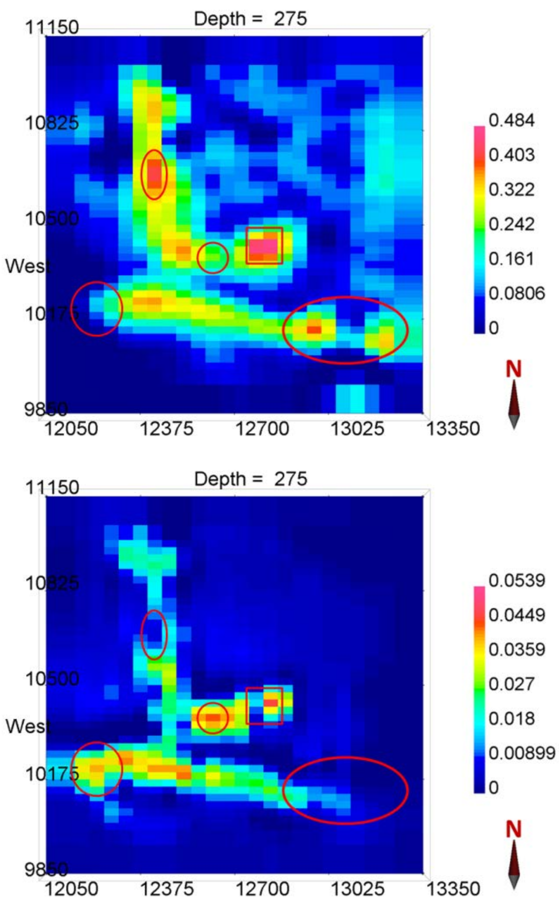

Figure 3: Depth slice of the separately inverted density model (a) and susceptibility model (b). Red rectangles mark the location of sulphide deposit. Red ellipses identify regions where density and susceptibility values show anti-correlations.

We first performed two separate inversions using standard smoothness constraints. Figure 3 shows a slice of the recovered density and susceptibility models at the depth of 275 m. The red rectangles in Figure 3a and 3b mark the massive sulphide deposit intersected by the drillholes. The high density contrast values within the rectangle in Figure 3a is expected, because the massive sulphide deposit has a much higher density value than the other rocks as indicated by Table 1. The recovered susceptibility values in the same rectangle in Figure 3b show both magnetic and non-magnetic materials. However, the petrophysical data in Table 1 associate massive sulphide with only high susceptibility values. The discrepancy between the simplified petrophysical data in Table 1 and the separately inverted geophysical models in Figure 3 can be explained by the fact that the sulphide deposit in the study area has two distinct metal zones: a non-magnetic Cu zone and a magnetic Pb-Zn zone. This was revealed by the drillholes, but not captured by the petrophysical data in Table 1.

The separately inverted models in Figure 3 also show large areas of dense and magnetic anomalies that are not associated with sulphide but with gabbroic intrusions. However, according to Table 1, gabbro should not produce such anomalies.

Based on the above analysis, it is clear that the petrophysical data in Table 1, which represents our first and overly simplified hypothesis about the petrophysics in the study area, do not accurately reflect the geology, and need to be rectified. Therefore, we proposed our second hypothesis, shown in Table 2, which incorporates our latest petrophysical knowledge. We then carried out a joint clustering inversion with all the petrophysical information in Table 2 incorporated.

Lithology	$\Delta\rho$ (g/cm^3)	Suscept. (10^{-3} SI)
Mafic intrusion	0-0.8	0-70
Metasediments	0	0
Felsic tuff	0	0
Magnetic sulphide	0.9	80
Non-magnetic VMS	0.9	0

Table 2: Second hypothesis about the physical property values based on known geology, drill-hole information and separate inversion results.

However, it turns out that the gravity data cannot be reproduced well. Also, the estimated density and susceptibility values contain unexpected clustering features. We then developed a third hypothesis (not shown here), and tested it by performing a similar joint clustering inversion. This testing process continues until our final hypothesis of 3 circular and 2 elliptical clusters. The joint clustering inversion driven by the last hypothesis results in two models that are in good agreement with all existing data. Figure 4 shows the lithology differentiation results from the final hypothesis.

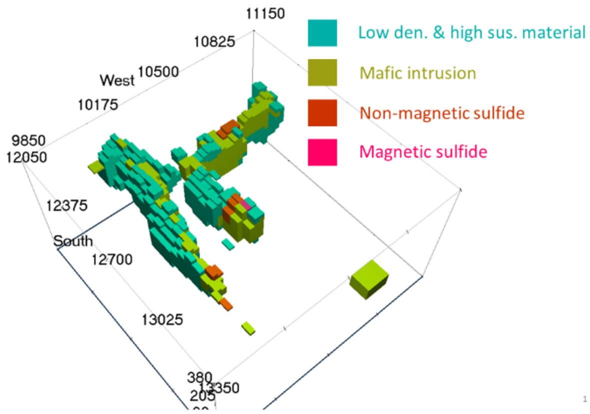

Figure 4: The 3D lithology differentiation results from the joint clustering inversion driven by the last hypothesis. Each color represents a unique lithological unit. Sediments and felsic rocks were removed because they represent the zero background.

CONCLUSIONS

Petrophysical data, as one type of geological data, have proven to provide valuable constraints for geophysical inversions. However, effectively incorporating statistical petrophysical data remains a challenge. The joint clustering inversion makes use of fuzzy clustering technique, and provides an effective means of utilizing statistical petrophysical data. Depending upon the availability and reliability of petrophysical data, the joint clustering inversion can be employed as either a direct imaging tool or an iterative hypothesis testing tool. In brownfield exploration, where reliable petrophysical data have been collected, the joint clustering inversion is able to produce an Earth model that is consistent with both the geophysical data and the petrophysical data. In greenfield exploration, where little reliable petrophysical information is available, we have shown that the joint clustering inversion serves as an effective tool for testing different petrophysical hypotheses or assumptions. We have demonstrated the use of joint clustering inversion in both situations with two field data examples. We conclude that the joint clustering inversion method is one effective way of integrating geophysical and petrophysical data and performing hypothesis testing.

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