INTEGRATION OF BOREHOLE DATA IN GEOPHYSICAL INVERSION USING FUZZY CLUSTERING

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SUMMARY

Borehole data is critical information to constrain geophysical inversions. Borehole information is usually used as a petrophysical constraint of the inversion scheme. Therefore, borehole information is only valuable if the borehole features are the same as the physical parameters of geophysical models. In fact, we may have many drilled holes, but the physical parameter of the geophysical model is only available in a few holes. Thus, the question is how we can exploit other borehole features to assist the inversion. We present an application of fuzzy clustering to incorporate multiple borehole features such as lithological, assay and wireline logs in the geophysical inversion. The integration of this extra information assist inversion process to build a model that fit surface geophysical data and simultaneously honour the prior information of borehole data. We apply this approach to the case study over the Kevitsa deposit within the Kevitsa ultramafic intrusion in northern Finland. The inversion of seismic reflection data with assistance from borehole information produces a more geologically interpretable image than seismic reflection data. The integration of both petrophysical and spatial attribute of the borehole enable the inversion to build a better model than only petrophysical constraint.

Key words: integration; fuzzy clustering; inversion; seismic; borehole.

INTRODUCTION

Geophysical inversion provides a powerful tool to build subsurface models. These models are then interpreted to build geological models. Critical issues of the inversion are non-unique solutions, that is, infinite models can adequately fit the data with a certain level of noise. Including prior structural and petrophysical information can reduce the ambiguity of the inversion (Meju, 1994). Lelièvre et al. (2009) stated an approach to include prior physical properties and structural information into deterministic inversion. Zhang and Revil (2015) used petrophysical relationships within each unit to constrain inversion of gravity and electrical resistivity data. The approach of Sun and Li (2016) is similar, they divide the inversion domain into subdomains, each area has a different clustering approach. Their work is based on the idea that the subsurface is usually separated into units of nearly uniform physical properties that may relate to rock groups.

Prior information from borehole data is usually cooperated in the geophysical inversion by using petrophysical constraint routines. These approaches include bound and trend constraints (Lelièvre et al., 2009), a reference model (Farquharson et al., 2008), and statistical information (Bosch et al., 2009; González et al., 2008; Sun and Li, 2013). The problem of all these schemes is they do not fully exploit information from borehole data. The bound and trend or statistical constraints only use physical parameters of the borehole and igore the spatial information. Using borehole data to generate the reference model require sufficient number of boreholes and a reasonable distribution of these, to reduce artefacts due to the intepolation process. These schemes are not applicable if the borehole data does not contain phyisical parameters related to the geophysical method. For example, if the borehole only contains resistivity data, this borehole data is useless for the inversion of seimsic or gravity data.

In this study, we present an approach that enables the inversion process to include both physical and spatial information of borehole data. Our constraint of the inversion is based on the unit assumption thought fuzzy clustering. We applied to the inversion of seismic reflection data using constraint from borehole information. The data set was acquired in the Kevitsa mine site, northern Finland, and includes 3D reflection seismic data and borehole data from 866 drilled holes. The location of the seismic acquisition and boreholes is presented in Figure 2. Details of the seismic data are provided in Malehmir et al. (2012). The borehole data includes the wireline logs, assay data, core measurements, and lithological information from 886 holes. The borehole data was also described by Neild (2015); Steel (2011).

METHOD AND RESULTS

Constraint geophysical inversion using fuzzy clustering

This algorithms is also described in (Kieu et al., 2016). Our inversion algorithm is formulated with the minimization of the following objective function (Sun and Li 2011):

$$\Phi = \Phi_d + \beta\Phi_m + \gamma\Phi_{FCM}, \tag{1}$$

where Φ_d measures the difference between observed data and the synthetic data from the inverted models, Φ_m represents the smooth constraint and Φ_{FCM} is the fuzzy c-means (FCM) objective function (equation 2). This "model guider" term directs the updating model process. More specifically, it drives the incorporation of rock units within the inverted model. The regularization parameters β and γ balance between misfit, model structure and FCM constraint terms.

Integration of borehole into the inversion

In this work, we utilise both constraints, petrophysics (Kieu and Kepic, 2015) and structure (Kieu et al., 2016). Prior petrophysical information is obtained by analysing wireline logs of P-wave velocity and density. Structural information is available from analysing geochemical data and lithology of the boreholes. These processes are performed by using fuzzy c-means clustering (Bezdek, 1981).

The prior petrophysical representative values are included in the inversion routine via FCM (Kieu and Kepic, 2015), which classifies N samples of a dataset $\mathbf{Z}(z_j)$ into C subsets based on feature similarities, driving the groups central value $\mathbf{V}(v_k)$ towards the prior representative conductivity $\mathbf{P}(p_k)$.

$$\Phi_{FCM} = (1-\eta)\sum_{j=1}^{N}\sum_{k=1}^{C} u_{jk}^{q}\left\|z_j - v_k\right\|_2^2 + \eta\sum_{k=1}^{C}\|p_k - v_k\|_2^2 \,, \tag{2}$$

where q is the fuzziness parameter, q>1, u_{jk} is the membership degree of sample jth belong to the kth cluster, with the constraint $\sum_{k=1}^{C} u_{jk} = 1$. η is the weighting value that represents the confidence level of the prior information.

The basic idea of including the borehole spatial information into our inversion procedure is demonstrated in Figure 1. If the properties of each seismic sample should be similar to the nearest borehole samples with a level of certainty. In this work, we weigh this certainty as follows:

$$Certainty = exp\left(-\frac{d}{\alpha}\right), \tag{3}$$

where d is the distance from a borehole to the seismic samples and α is a scaling factor that controls the radius of influence of borehole data to the vicinity.

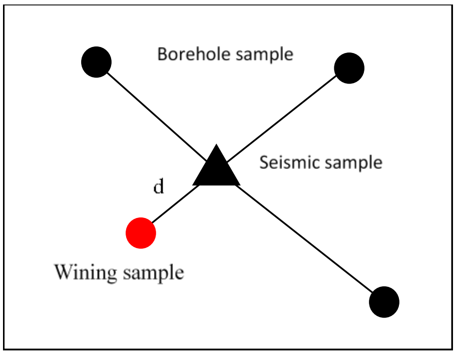


Figure 1: Schematic shows the concept of including borehole information in the seismic inversion process via fuzzy clustering. We assume that the seismic sample information is like that from the closest borehole sample (namely the wining sample). The certainty of similarity between the seismic sample and the borehole sample is defined based on the distance, d, between them (equation 3).

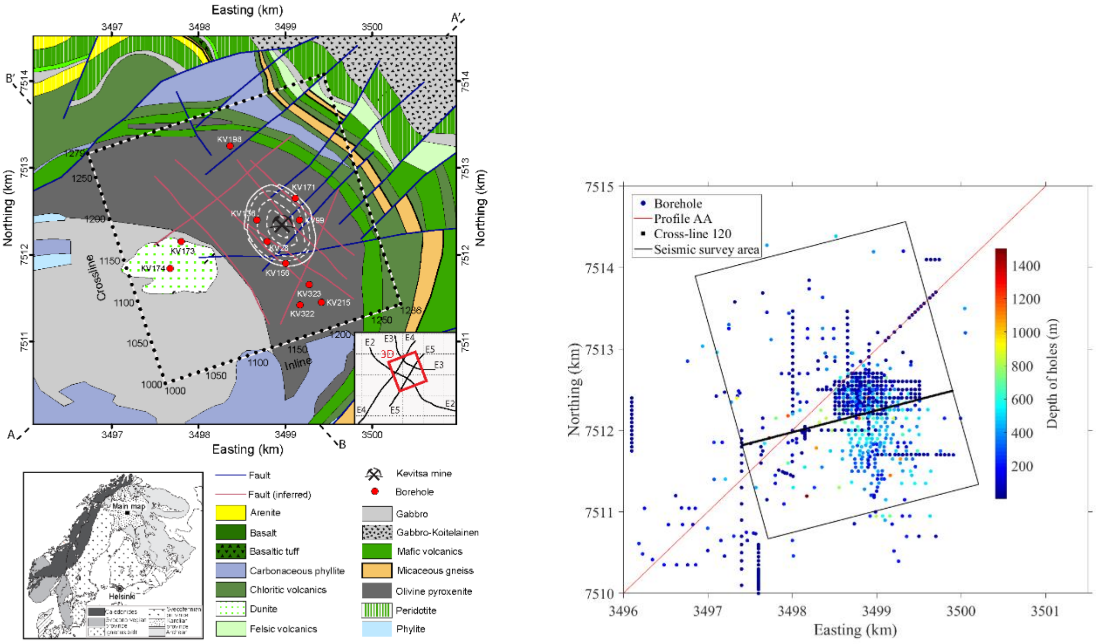
To integrate spatial information of the borehole within the inversion via FCM, the spatial information **b** is combined with the model parameter **m** to form the data input **Z=[m b]** of clustering process. The certainty of spatial information is accounted for in fuzzy cluster process the same as boundary information in Kieu et al. (2016). Figure 3 displays the "certainty" of projected borehole samples on seismic samples. Certainty and collaborative clustering can integrate directly with borehole data in the inversion. In this case, the borehole data cluster information plays the same role as spatial information, as described in (Kieu et al., 2016). This spatial information is obtained by a clustering process of the Co, Cu and Ni assay data and lithology from all holes (Figure 4).

Inversion of Kevitsa data set

The seismic inversion routine in this work is same as the inversion process described in (Kieu et al., 2016; Kieu and Kepic, 2015). The difference here is the manner in which the prior information is included in the inversion. The inversion results without and with borehole assay data constraints are named Inv#1 (without elemental cluster constraints) and Inv#2 (with borehole assay constraints) respectively.

The validation of the inversion results is demonstrated in Figure 5. The general trend of the initial model still exists in the inverted model, but the inverted result of Inv#2 illustrates a better fit to the borehole data than that of Inv#1. Particularly at depths from 500 to 700 m, the results of Inv#1 show a high bias compared to the borehole data. This may be due to overfitting to seismic data where we have a very strong reflection signal caused by previous data processing and imperfect wavelet extraction in the inversion process. Model Inv#2, obtained by including spatial information from the boreholes through projection of the clustering results, has less overfit effects (residual seismic wavelet still in the volume) and appears to produce similar results with less artefacts.

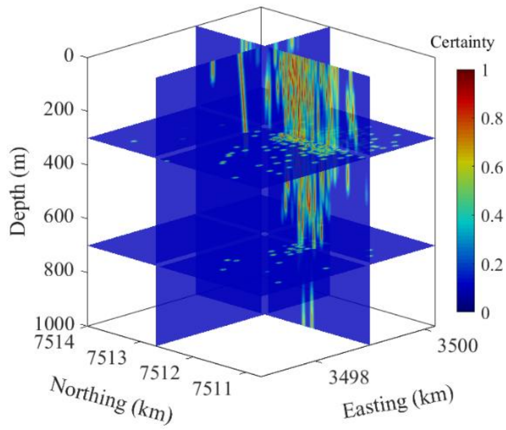
Figure 6 presents a comparison between our results and a migrated seismic section with a interpreted geological section based on the results of 2D and 3D seismic interpretation by Koivisto et al. (2015) along south-west to north-east section (AA'). Clearly, the raw seismic data is more challenging to interpret than the acoustic impedance and pseudo-lithology section, since the reflection seismic section only contains the boundaries. The interpretation by Koivisto et al. (2015) and others is performed by picking the boundaries first then selecting the rock unit by referring to nearby borehole data. This not too dissimilar to what the FCM inversion process described in this work does when the seismic data does not have enough low frequency data to be able to confidently select one model over another. They also state that the continuity of the boundaries is poor and the high velocities with resultant variation in depth-location result in interpretation issues. The boundaries can also be improperly defined because of ambiguity. In contrast, the inverted images tend to produce geological images that should be significantly easier to interpret. For instance, the boundary between the Dunite and Kevitsa intrusion (Figure 6a) is very ambiguously defined according to the seismic data only (Figure 6b), as in the work of Koivisto et al. (2015). This boundary may be redefined based on our results (Figure 6c and d).



(a) **(b)**

Figure 2: (a) Geological map (After Malehmir et al. (2012)). (b) Map of borehole and seismic data locations. The colour of the dots shows the depth of hole. The deep holes (>500 m) are located in the centre of mine site, the north of the seismic survey areas show less dense holes, most of which are shallow. The red line marks the location of profile AA' used to compared my results with ones obtained by (Koivisto et al., 2015).

Figure 3: The certainty of including borehole data in the seismic inversion process is calculated using equation (3).



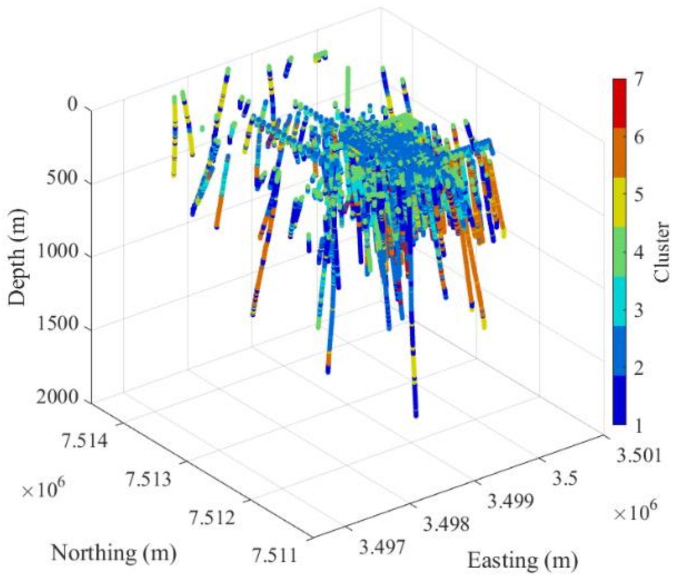


Figure 4: Clustering results from the borhole data including Co, Cu, Ni, and lithology.

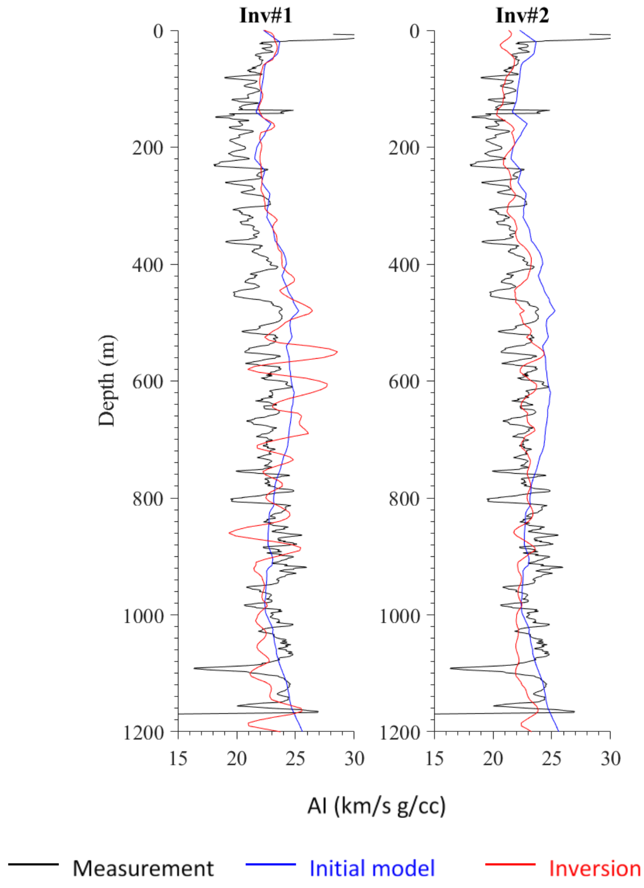


Figure 5: Comparison of inversion models and borehole data in the KV28 borehole. Generally, the inversion results match with the borehole data trend. The inclusion of clustering information using the borehole data in Inv#2 results in a better quality inversion than the ones processed without the borehole constraints.

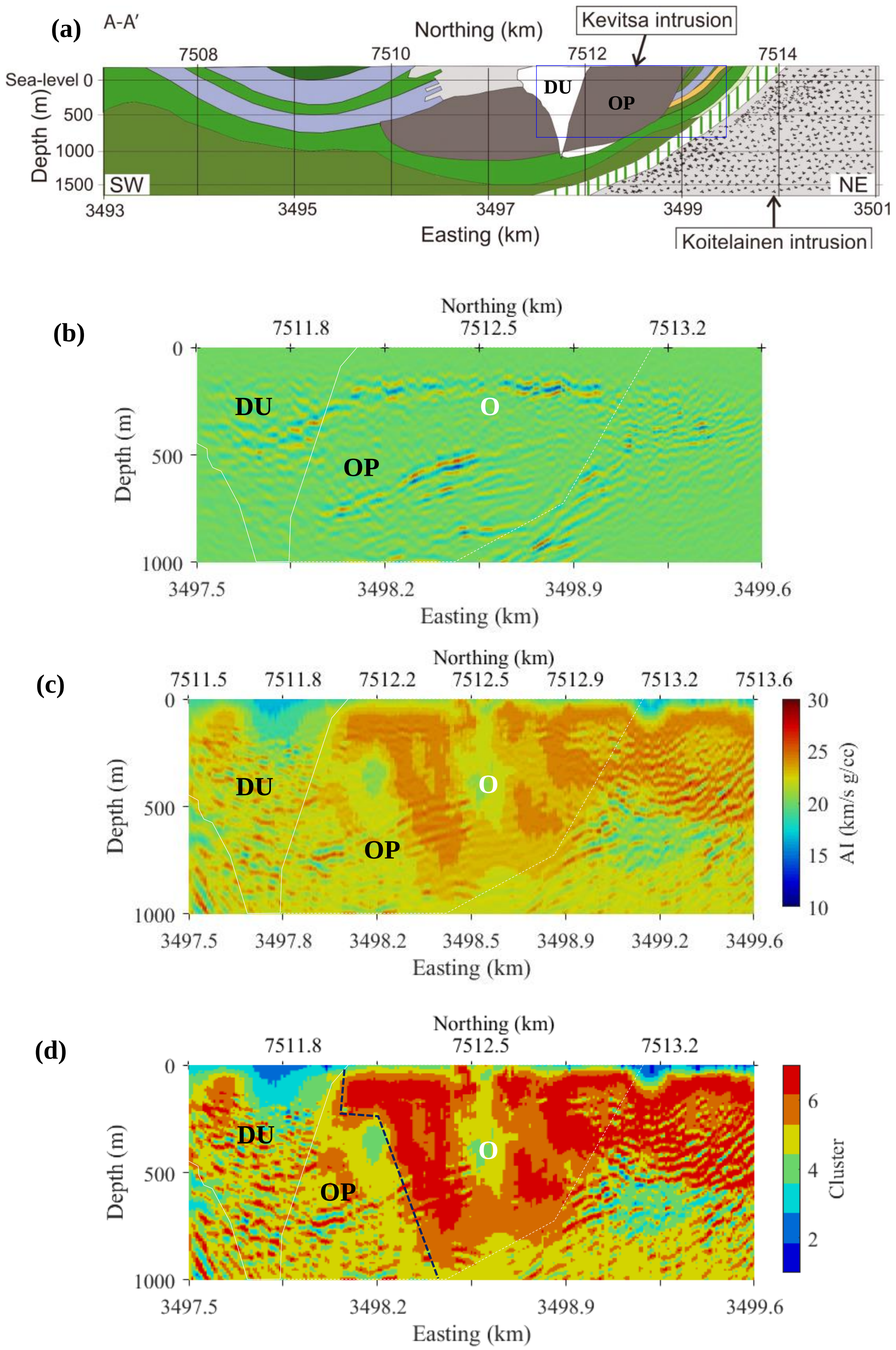


Figure 6: (a) Geological section along the profile AA' (Figure 2) (after Koivisto et al. (2015)). The blue rectangle marks the area of our sections. In this interpretation, we concentrate on two areas marked by DU (Dunite) and OP (Olivine pyroxenite). (b) Migrated seismic data along the section AA'. (c) Acoustic impedance section from the inversion Inv#2. (d) Clustering (pseudo-lithology) model from the inverted model. The dashed and solid white lines show the boundaries of DU and OP zones respectively. The dashed black line is probably a new boundary between DU and OP zones. O marks the ore zone.

CONCLUSIONS

Both petrophysical and spatial features of the borehole data can contribute to constrain the inversion of seismic reflection data. We utilise the ability of fuzzy clustering to integrate all the available downhole data into the seismic inversion routine, and not just the parameter of interest. The inverted results can assist with geological interpretation. This strategy should be applicable to other data sets.

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